Power and Bandwidth allocation for High-Throughput Satellites using Particle Swarm Optimization

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Abstract

In the recent years, communications satellites have been evolving from static payloads to highly flexible components. Modern satellites are able to provide four orders of magnitude higher throughput than their ancestors fourty years ago, going from the few Mbps with the first commercial communication satellite to the hundreds of Gbps of current approaches. This enhancement in performance aims to cover an ever-increasing highly variable demand. An automatic tool able to dynamically manage the satellites' resources, despite optional in the early years of this industry, has become a necessity.

Academic interest in the resource allocation problem for satellite communications has been growing in the last years. Previous literature show successful implementations of a vast variety of algorithms (mathematical programming, heuristic and metaheuristic approaches, etc) for the separate power and bandwidth allocation problems. Some research has also been focused on the joint problem, but the number of implementations is low. Moreover, the number of successful implementations is furtherly reduced when considering time restrictions. This thesis aims to provide a new implementation of a metaheuristic, commonly known to be fast, to solve the joint power and bandwidth allocation in a real case scenario, where the time restrictions are a constraint.

To do so, the satellite communications context in first introduced. Then, the joint problem, including the variables, restrictions and metrics, is formulated and the simulation model is explained. At this point, the Particle Swarm Optimization implementation is provided and each of the functionalities of the algorithm is explained and detailed.

The results show a fast convergence of the implementation, reaching a *good enough* solution in under 10s, but getting stuck in a local optima. To solve this problem, a hybrid version of the algorithm combined with a genetic algorithm is developed. The new results show that the hybrid is a well suited implementation for the power allocation problem, as it consistently improves the GA-only results. For the joint problem, it provides an 80% power reduction and 2% lower unmet demand than the GA-only in the low runtime scenario.

Keywords: Satellite Communications, Resource Allocation, Metaheuristic, Particle Swarm Optimization, Hybrid

Resum

En els últims anys, els satèl·lits de comunicacions han evolucionat des d'una càrrega útil estàtica fins a components completament dinàmics. Els satèl·lits moderns són capaços de proveir quatre ordres de magnitud més *data rate* que els seus predecessors quaranta anys abans, anant des dels pocs Mbps amb el primer satèl·lit de comunicacions comercial fins als centenars de Gbps dels darrers plantejaments. Aquest increment en rendiment intenta cobrir una sempre creixent i canviant demanda. Una eina automàtica capaç de gestionar dinàmicament els recursos dels satèl·lits, tot i que opcional en els primers anys d'aquesta indústria, és ara una necessitat.

L'interès acadèmic en el problema d'assignació de recursos en un satèl·lit ha crescut els últims anys. Literatura prèvia mostra implementacions exitoses d'una gran varietat d'algoritmes (programació matemàtica, plantejaments heurístics i metaheurístics, etc) pels problemes d'assignació de potència i d'ample de banda. Alguns treballs també s'han centrat en el problema conjunt, però el nombre d'implementacions és baix. A més a més, el nombre d'implementacions exitoses és encara més reduït quan es consideren restriccions temporals. Aquesta tesis té com a objectiu proporcionar una nova implementació d'una metaheurística, coneguda per la seva ràpida convergència, per solucionar el problema conjunt d'assignació de potència i ample de banda en un escenari real, on les restriccions temporals estan a l'ordre del dia.

Amb aquest objectiu, primer s'introdueix el context de comunicacions de satèl·lits. Seguidament, es formula el problema conjunt, incloent les variables, restriccions i mètriques, i s'explica el model de simulació. En aquest moment, es proveeix la implementació del Particle Swarm Optimization i s'expliquen i detallen cada una de les funcionalitats de l'algoritme.

Els resultats mostren una ràpida convergència de la implementació, aconseguint una *suficientment bona* solució en menys de 10s, però convergint a un òptim local. Per solucionar aquest problema, es desenvolupa una versió híbrida de l'algoritme, combinant-lo amb un Genetic Algorithm. Els nous resultats mostren que l'híbrid és un algoritme adequat per resoldre el problema de l'assignació de potència, ja que, de manera consistent, millora els resultats de la implementació del GA. Pel problema conjunt, proporciona un 80% de reducció de potència i un 2% de reducció en demanda no satisfeta en escenaris de baix temps d'execució.

Paraules clau: Comunicacions de satèl·lits, Assignació de recursos, Metaheurística, Particle Swarm Optimization, Híbrid

Resumen

En los últimos años, los satélites de comunicaciones han evolucionado desde una carga útil estática hasta componentes enteramente dinámicos. Los satélites modernos son capaces de proveer cuatro órdenes de magnitud más *data rate* que sus predecesores cuarenta años antes, pasando de los pocos Mbps con el primer satélite de comunicaciones comercial hasta los centenares de Gbps de los últimos planteamientos. Este incremento en rendimiento intenta cubrir una siempre creciente y cambiante demanda. Una herramienta capaz de gestionar dinámicamente los recursos de los satélites, aunque opcional en los primeros años de esta industria, es ahora una necesidad.

En interés académico en el problema de asignación de recursos en un satélite ha crecido en los últimos años. Literatura previa muestra implementaciones exitosas de una gran variedad de algoritmos (programación matemática, planteamientos heurísticos y metaheurísticos, etc) para los problemas de asignación de potencia y ancho de banda. Algunos trabajos también se han centrado en el problema conjunto, pero el número de implementaciones es bajo. Además, el nombre de implementaciones exitosas es aún más reducido cuando se consideran restricciones temporales. Esta tesis tiene como objetivo proporcionar una nueva implementación de una metaheurística, conocida por su rápida convergencia, para solucionar el problema conjunto de asignación de potencia i ancho de banda en un escenario real, donde las restricciones temporales están a la orden del dia.

Con este objetivo, primero se introduce el contexto de comunicaciones de satélites. Seguidamente, se formula el problema conjunto, incluyendo las variables, restricciones y métricas, y se explica el modelo de simulación. En este momento, se provee la implementación del Particle Swarm Optimization y se explican y detallan cada una de las funcionalidades del algoritmo.

Los resultados muestran una rápida convergencia de la implementación, consiguiendo una *suficientemente buena* solución en menos de 10s, pero convergiendo a un mínimo local. Para solucionar este problema, se desarrolla una versión híbrida del algoritmo, combinándolo con un Genetic Algorithm. Los nuevos resultados muestran que el híbrido es un algoritmo adecuado para resolver el problema de asignación de potencia, ya que, de manera consistente, mejora los resultados de la implementación del GA. Para el problema conjunto, proporciona un 80% de reducción en potencia y un 2% de reducción en demanda no satisfecha en escenarios de bajo tiempo de ejecución.

Palabras clave: Comunicaciones de satélites, Asignación de recursos, Metaheurística, Particle Swarm Optimization, Híbrido

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Nomenclature

Acronyms

GA Genetic Algorithm

ITU International Telecommunication Union

MD Met Demand

$MODCOD$ Modulation and Coding

PSO Particle Swarm Optimization

$SINR$ Signal to Interference plus Noise Ratio

UD Unmet Demand

Common sub-indices

$3dB$ Value in the 3dB threshold

R Receiving antenna

T Transmitting antenna

u User

Symbols

Γ Spectral efficiency

λ Wavelength

θ Angle with reference to the beam pointing

A Area

c Speed of light

D Antenna diameter

f Frequency

G Gain

k Boltzmann constant

N Noise power

P Power

R Data rate

r Antenna radius

T Temperature

W Watt

Chapter 1

Introduction

1.1 Motivation

Since its beginnings in the early 60s, the satellite communications market has experienced an exponential growth which does not seem to stop any time soon. While in the early years of this industry a communications satellite was only able to manage a few phone lines (few Mbps), a rapid evolution of on-board technology and an increase in power generation led to the development of the so-called High-Throughput Satellites (HTS), able to provide tens and even hundreds of Gbps. According to recent reports [4][5], the growth in demand is expected to continue over the next years.

The growth in the first decades of the industry was heavily boosted by an increase the launcher's capacity, allowing higher power generation, which is directly related with the satellite's capacity. This factor, however, eclipsed the impact of the payload's technology evolution. In the last decades, however, the launcher's capacity growth has seemed to stall while the development of on-board payload has become crucial to maintain the growth imposed by the demand.

Within early stages of this industry, those resources where assigned once, prior to the launch of the satellite, directly depending on the contract signed with the users. This works perfectly when the users consume exactly the amount of data rate demanded at every time. However, the harsh reality is that the data consumed is bursty. The nature of current systems is based on highly fluctuating consumption, as it depends on single individuals' behaviour. The static assignation of resources incurs in a waste of power and bandwidth when the demand is not maximal, which happens frequently. To solve this problem, satellite manufacturers have developed highly flexible payloads able to change the assignation of resources much more often than once in a lifetime. Thanks to recent technology improvements, satellite's payload have evolved from static preassigned resources to fully dynamic components, able to change their behaviour based on on-ground command. As an example, current satellite operators are planning to launch new constellations able to manage thousands of fully re-configurable beams (multi-beam architectures), while able to change frequency and power on command.

While this allows for a better satisfaction of the demand, both in terms of quality of service and revenues, it comes at the expense of a higher complexity in the dynamic management. Although manual resource allocation was well suited for static management, it is unfeasible for the new generation of satellite communications. An automatic tool has to be developed to fully exploit the novel capabilities. The problem underlying the development of this tool is known as the resource allocation (RA) problem.

1.2 General objectives

The main purpose of this thesis is to solve the allocation of power and bandwidth within the RA problem for High-throughput multibeam Satellites. To this end, this thesis proposes the application of a new algorithm to solve the joint problem. Finally, this work compares and tests the new implementation against a predefined baseline.

1.3 Background

The Resource Allocation (RA) problem in the context of satellite communications has been profoundly studied in the recent years. Within the RA problem, literature often identifies four resources to allocate: radio-transmitted power, radio-transmission frequency, beam pointing and beam shape. For this thesis, the literature review is divided in three parts: power allocation, frequency assignment and the joint problem. The following paragraphs comprise the work for each of these fields.

The power allocation problem consists of assigning the power level for each transmitting beam within a satellite. The problem is known to be NP-hard and hard to approximate when the satellite's power generation is not enough to satisfy the power demand [6]. In the recent years, many approaches have been developed to solve this problem. Authors in [7] propose a convex optimization technique to find the trade-off between system capacity and the fairness between users. Work [8] tries to find a solution with a heuristic based on Lagrange multipliers. Regarding more modern techniques, [6] uses a hybrid between the Simmulated Annealing and Genetic Algorithm metaheuristics to solve a multiobjective formulation of the problem, while [9] uses a Particle Swarm Optimization Approach to solve a single objective formulation. The authors in [10] rely on a Deep Reinforcement Learning technique to find a solution. All these studies try to distribute the available power pool into different carriers and beams to meet users' demand.

The frequency assignment problem consists of dividing the frequency pool, either in the frequency domain (*beam coloring*) or in the time domain (*beam hopping*), among beams to fulfil the demand of each user. As the power allocation problem, the frequency assignment is known to be NP hard and hard to approximate [11]. Starting with mathematical programming, this problem has also been solved using heuristic approaches [12] and convex optimization [13]. Regarding artificial intelligence and machine learning approaches, [14] proposes a deep reinforcement learning methodology, while [15] uses a hybrid neural network combined with a Genetic Algorithm.

Both problems have also been studied together in recent literature. Authors in [16] propose an algorithm to minimize co-channel interference. This problem has also been studied in [17] following a Genetic Algorithm approach. Both works show significant improvements in power when allocating joint power and bandwidth compared to only power allocation. None of this works, however, tests the algorithms under time restriction conditions, crucial for real applications.

1.4 Specific objective

The specific purpose of this thesis is to solve the joint power and bandwidth allocation problem for multibeam HTS by formulating the problem as a multi-objective problem and solving it using Particle Swarm Optimization (PSO). To this purpose, this thesis presents this new implementation of the algorithm for the joint problem, while benchmarking the algorithm for several test cases in a realistic environment.

1.5 Overview

The following lines give a general overview of this thesis and its main sections.

Chapter 2 gives a brief introduction of the Satellite Communication context. The main elements that interact in a communication are explained in section 2.1. The equations that govern the system are presented in section 2.2. Finally, the the metric used in this work for satellite communications systems is introduced in 2.3.

Chapter 3 describes the model used to formulate and solve the problem. The formulation, metrics and variables used are presented in section 3.1. A short grasp to the simulation model is given in section 3.2.

Chapter 4 gives a detailed explanation of the metaheuristic used to solve the problem, as well as a secondary metaheuristic used to compare the solution space. The Particle Swarm Optimization algorithm and its implementation is discussed in section 4.1. An overview of the Genetic Algorithm is given in section 4.2.

Chapter 5 presents and discusses the results of this thesis. Refer to sections 5.3 and 5.4 for the three studied scenarios.

Chapter 6 concludes with the main findings of this thesis and its implications in future work.

Chapter 2

Satellite Communications System

Information theory, presented in [18] over 50 years ago, mathematically describes the entities and relations in a general communication system. As a general overview, it exposes 6 elements that take part in the information's flow:

- *Information Source*: starting point of the communication.
- *Transmitter*: element in charge of emitting the message.
- *Transmitting Medium*: physical link between transmitter and receiver.
- *Receiver*: element in charge of receiving the message.
- *Destination*: end point of the communication.
- *Noise Source*: interference in the message due to disturbances in the Transmitting Medium.

The flow of this system is clear and is the source of the known diagram shown in figure 2.1.

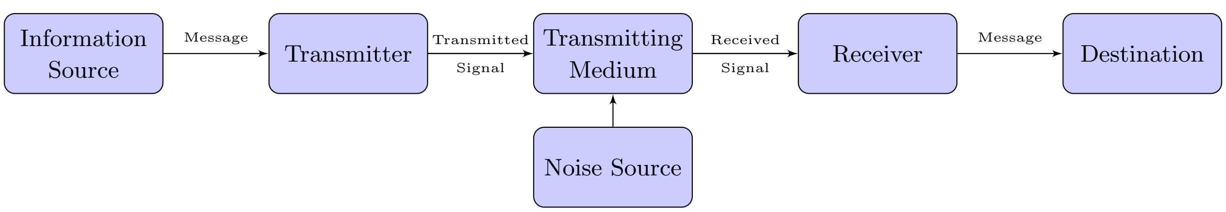


Figure 2.1: Information Theory Diagram

Space communications accurately follow the description presented in [18]. In the following lines, an introduction and brief explanation of all the elements will be given while the laws and equations that govern the system will be presented and explained. [1]

[1] This thesis briefly resumes the information presented in [3]. Refer to this source for further clarification.

2.1 Information theory applied to space communications

Space communications are vastly governed by two interlocutors: ground stations and satellites. Ground stations are entities located in the surface of the Earth that demand a flow of communication. Satellites, on the other hand, are entities located in orbits around the Earth in charge of satisfying this demand. These two entities are associated with the endpoints of the communication (source and destination). The exact mapping depends on the direction of the information. Standardization defines the following directions:

- *Uplink*: from ground stations (source) to satellites (destination).
- *Downlink*: from satellites (source) to ground stations (destination).
- *Intersatellite links*: between satellites.

In order to get the information from the source to the destination, space communications rely on antennas. Antennas are devices able to convert electric signals into electromagnetic waves and vice-versa. Each endpoint, then, requires an antenna to establish the communication. Following this definition, antennas fulfil the roles of transmitting and receiving entities, as their main function is to interact the endpoints with the medium.

From the description of antennas, it can be seen that the Transmitting Medium is the electromagnetic space between the two antennas. The noise, then, are the disturbances in this electromagnetic space.

With all the elements described, the mapping of figure 2.1 to space communications can be directly done:

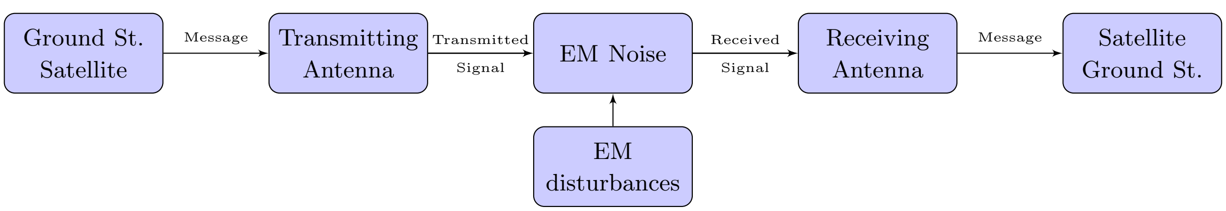


Figure 2.2: Information Theory applied to Space Communications (EM: Electromagnetic)

2.1.1 Channel: electromagnetic sub-space

The electromagnetic waves are responsible of transmitting the information from the transmitter to the receiver. These waves are primarily defined by three factors:

- *Power*: determines the wave's travel distance. This parameter is crucial for satellite communications as it restricts the wave's reachable destinations.

- *Frequency*: Rate of oscillation of the signal. Due to the limitation in the accessible frequencies, an international organization (International Telecommunication Union, ITU) is responsible of dividing the frequency space into the different sectors that use it. For space communications, the ITU has assigned different bands (figure 2.3), which are further subdivided into channels. This thesis assumes the utilization of the Ka band (26.5 - 40GHz) for the communications. Channels are arbitrarily defined sub-bands of the frequency space that have an ideal maximum throughput related to the bandwidth associated. Therefore, the system's capacity is directly related with the number of channels in use and the bandwidth of each channel.

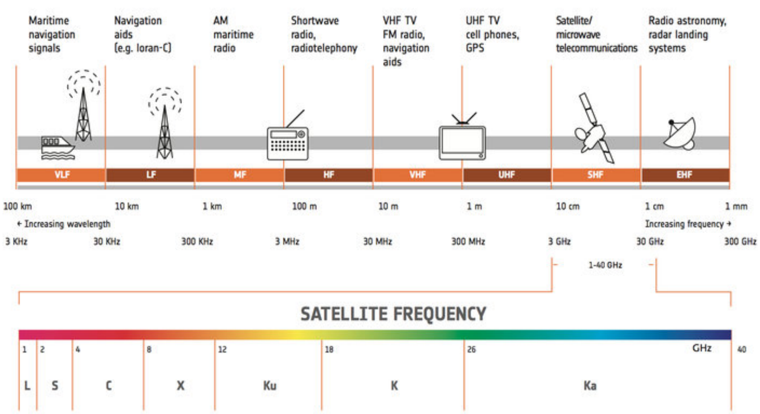


Figure 2.3: Division of frequency spectrum [1]

- *Polarization*: Any electromagnetic wave is composed by an electric field component and a magnetic field component. These two components are orthogonal and perpendicular to the propagation of the wave. The direction of these fields is arbitrary, defined by the emitting antenna. Any antenna that transmits or receives in a particular direction cannot transmit or receive in the opposite one. This permits doubling the effective bandwidth of the communication, as two opposite polarizations can be transmitted without any interference between them. Figure 2.4 shows a single wave polarization. Neither the electric, nor the magnetic field interfere when the fields are orthogonal.

2.1.2 Antennas

An antenna is a device that converts an electrical signal into an electromagnetic wave and vice versa. Antennas are defined by two main parameters: gain and beamwidth, which determine the exact behaviour of the wave transmitted.

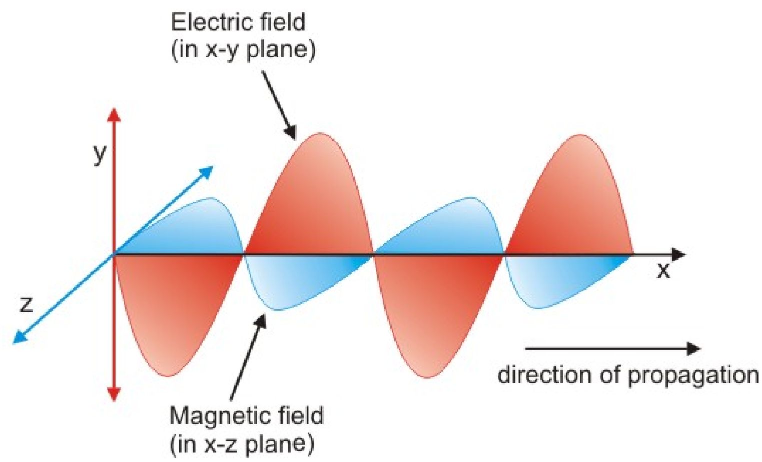


Figure 2.4: Example of a linear polarization [2]

Gain

Ratio of power transmitted or received per unit of solid angle with respect to the power transmitted or received per unit of solid angle by an isotropic antenna. Common antennas focus their power into a single or a subset of directions, which amplifies the power in those directions and reduces it in the others. Depending of the characteristics of the gain, different sub types of antennas are defined:

- *Isotropic*: power in all directions is the same.
- *Torus*: increased power in a plane.
- *Parabolic*: increased power in a single direction.

The parabolic antenna is the most used in space communications, as the power requirements are very restrictive and the position of the receiving antenna is known. The gain, thus, depends on the direction considered and is maximized in the electromagnetic axis of the antenna (boresight). For parabolic antennas, the maximum gain is obtained by:

$$G_{max} = \frac{4\pi}{\lambda^2} A_{eff} \tag{2.1}$$

Where λ is the wavelength and A_{eff} is the effective area of the antenna. The latter parameter can be computed using the area of the antenna ($A = \frac{\pi D^2}{4}$) and an efficiency parameter based on the imperfections of the antenna (shape, obstacles, etc).

Beamwidth

The beamwidth defines the pattern of the gain in the different directions. In the parabolic antenna, the gain is focused in a single direction, but some directions still have residual gain:

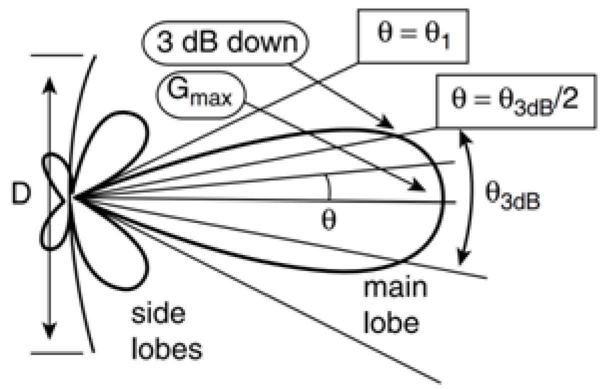


Figure 2.5: Gain of a parabolic antenna [3]

As can be seen in 2.5, the gain is lobe-shaped and rapidly decays after the 3dB limit. That is, when computing the gain in dB ($G(dB) = 10log(G)$), the gain loss rapidly increases when surpassing the limit $G = G_{max} - 3dB$. Therefore, the range of the antenna lies within this margin (which produces a circular shape). This is called the beamwidth. Current technology allows multiple beams per antenna, each with its own pointing and beamwidth. Also, modern approaches permit other shapes in the beam, but its technology and applications are outside the range of this thesis.

The angle of 3dB can be computed as

$$\theta_{3dB} = 70\frac{\lambda}{D}\ [rad] \tag{2.2}$$

The gain with respect to θ_{3dB} can be adjusted to the formula:

$$G(\theta) = G_{max} - 12\left(\frac{\theta}{\theta_{3dB}}\right)^2\ [dB] \tag{2.3}$$

For sufficiently small angles ($0 < \theta < \frac{\theta_{3dB}}{2}$)

Antenna sub-systems

Although antennas have a fundamental role in space communications, they require from other devices to properly work. Within those, the following are usually found:

- *Modulators*: electronic systems capable of codifying a signal into an electronic wave, using a specific MODCOD.
- *Demodulators*: inverse of modulators. These systems can be found in receiver antennas, which must first decode the wave to obtain the signal.
- *Power amplifiers*: electric systems capable of amplifying the power of an electromagnetic wave.
- *Signal processors*: electronic systems in charge of the signal processing needed to perform the communication.

2.2 Link budget equation: calculating the receiving power

One of the most important factors in the design of a space communication system is the power that will be fed to the transmitting antenna. This value directly influences the power received at the receiving antenna, which must be higher that the surrounding power level in order to correctly identify the signal.

With the defined gain parameter, the power transmitted is straight-forward to compute:

$$G_T P_T [W] \tag{2.4}$$

Where P_T is the power radiated by an isotropic antenna, which is directly the power that feeds the antenna. As the gain depends on the direction, is useful to characterize the power per unit of solid angle:

$$\frac{G_T P_T}{4\pi} \left[\frac{W}{steradian} \right] \tag{2.5}$$

A receiver antenna with area A located at a distance r would be defined by a solid angle equal to:

$$\frac{A}{r^2} [steradian] \tag{2.6}$$

Thus, the received power in the destination antenna would be equal to:

$$P_R = \frac{G_T P_T}{4\pi} \frac{A_R}{r^2} [W] \tag{2.7}$$

Where G_T can be assumed to be constant for $\frac{A_R}{r^2} << 1$.

The receiver antenna is also defined by its gain and efficiency. Therefore:

$$P_R = \frac{G_T P_T}{4\pi} \frac{1}{r^2} \frac{G_R}{\frac{4\pi}{\lambda^2}} [W] \tag{2.8}$$

At this point, we can define the free space loss as $L_{FS} = \left(\frac{4\pi r}{\lambda}\right)^2$. The receiving power is then:

$$P_R = \frac{G_T G_R}{L_{FS}} P_T [W] \tag{2.9}$$

This is known as the link budget equation. Usually, this formula is written in logarithmic form:

$$P_R = P_T + G_T + G_R - L \tag{2.10}$$

Where $X(dB) = 10log(X)$

Due to the imperfections in the chain, the free space loss is not the only loss of the system. Electrical, thermal and other losses also degrade the quality of the link. It is notable that in this equation all the losses have been unified in a single term L. In section 2.2.1, an explanation for all the losses, except for the already explained L_{FS}, can be found.

2.2.1 Electromagnetic disturbances

In order to be functional, receiving antennas have to be able to identify the signal from the received wave. To do so, the power of the wave has to be higher than the power of the surrounding noise. Thus, the ratio of signal power versus the noise power is a valuable metric to assess the correct identification of the signal. This leads to the necessity of the noise characterization.

Noise is commonly defined as random interferences within a signal. This is translated to a change in the frequencies observed by the receiver. Thus, the noise can be defined by:

$$N = N_0 B [W] \tag{2.11}$$

Where N is the noise power, N_0 the white noise power (random signal with equal intensity in all frequencies), and B the bandwidth of the signal.

In order to assimilate random noise with a physical meaning, the term noise temperature is used. Noise temperature is defined as:

$$T = \frac{N_0}{k} \tag{2.12}$$

Where k is the Boltzmann constant. This temperature T is the temperature at which a resistor produces the noise N_0.

Characterizing the noise for a single element simply becomes knowing its analog noise temperature. Modern systems, however, rely on a succession of elements to work and therefore it is necessary to characterize the noise in an aggregation of subsystems. To do so, the amplification in those subsystems must be considered. For example, if the first subsystem amplifies the signal, the relative noise of the second system would be lower, as the intensity of the signal would be higher. This can be written as:

$$T_{system} = T_1 + \frac{T_2}{G_1} + \frac{T_3}{G_1 G_2} + ... \tag{2.13}$$

Where T_{system} is the noise temperature level of the system, T_i is the increase in temperature introduced by the element i and G_i is the amplification in power in the element i. The equation shows that it is useful to have a low noise amplifier prior to the system, as it will reduce the noise for the rest of elements.

Noise sources

In order to correctly identify the amount of noise we can encounter in the system, the different sources in the space context must be known:

- *Atmospheric noise*: some atmospheric layers absorb and/or emit electromagnetic signals. Therefore, they act as losses and noise sources.
- *Thermal noise*: electromagnetic noise produced by the electronic systems near the antenna. The temperature of the antenna is defined by the sum of the atmospheric noise and the ground noise.
- *Electrical receiver*: noise introduced by the electrical wires due to their resistance.
- *Receiver*: noise introduced when amplifying the signal.
- *Attenuators*: some weather conditions, as well as other disturbances, act as attenuators of the signal. This elements, instead of acting as an additional element, increase all the other noises of the system. The temperature increase is defined by $T = (L-1)T_{ATT}$ where L is the attenuation due to the specific condition, T_{ATT} is the temperature prior to the condition and T is the increase in temperature. Thus, rain and meteorological formations may heavily affect the quality of the signal.

The combination of the temperatures of each source results in a global system temperature T. The noise power can thus be defined as $N = kTB$, k being the Boltzmann constant and B the bandwidth of the signal.

Interferences

In addition to noise sources, interferences between antennas and between beams are also relevant. As physics states, if two electromagnetic waves that work in the same frequency band and with the same polarization collide, the resulting signal will be a combination of both waves, thus being unable to extract the initial information. This is known as electromagnetic interference and the sources must be known and controlled in order to avoid them. The most common interference types are:

- *Carrier to adjacent beam interference* (CABI): two beams from the same antenna point to near locations and occupy the same frequency band and polarization. As the interference comes from the same antenna, can be computed and avoided.
- *Carrier to adjacent satellites interference* (CASI): two near satellites have beams pointing to near locations that operate in the same band and polarization. This is difficult to compute as the traffic parameters of other satellites is usually not known. Cooperation between operators is necessary to avoid it.
- *Carrier cross polarization interference* (CXPI): occurs when a fraction of the orthogonal-polarization signals interfere with the beam under study. Is usually difficult to compute as is a result of cross polarization waves and depolarization effects.
- *Carrier to third order inter-modulation products of interference* (C3IM): occurs due to non-linearities in the signal transformation chain in nearby beams that operate at similar frequencies. The transformation chain produces residual signals in nearby frequencies that may interfere with other waves.

Losses

While noise and interference affect the quality of the electromagnetic environment, losses directly disrupt the quality of the transmitted signal, reducing the effective power fed to the antenna. Losses appear due to imperfections in the system and must be avoided to minimize the waste of power in the communication. The most common types of losses are:

- *Electrical loss*: A part from the losses in efficiency due to shapes and obstacles, antennas also suffer from losses in the electrical circuits. These losses are small, but add a term to the equation (L_{TX} for the transmitter and L_{RX} for the receiver).
- *Depointing loss*: Usually, the antennas are not perfectly aligned with each other. Therefore the gain is not maximized, which can be interpreted as an additional loss.

  $$L = 12\left(\frac{\theta}{\theta_{3dB}}\right)^2 \tag{2.14}$$

  This can be computed for both antennas, leading to 2 new losses: L_T and L_X.
- *Polarization loss*: This loss only occurs if the receiving antenna is not correctly oriented with the polarization of the field. This can be due to a mounting error or a mismatch in the signal due to atmospheric depolarization. This loss is included in the formula with the symbol L_{POL}.
- *Atmospheric loss*: The diverse layers of the atmosphere are usually source of losses, due to the energy necessary to cross these regions. The *travel loss*, thus, composes of L_{FS} and L_A.

2.2.2 Signal to noise ratio

Taking all this into account, the link budget equation results in:

$$P_R = P_T + G_T + G_R - L_{FS} - L_{TX} - L_{RX} - L_T - L_R - L_{POL} - L_A \; [dB] \tag{2.15}$$

This equation computes the power in the receiving antenna transported by the wave (also known as carrier). In order to determine if this power is enough to distinguish the information from the surrounding noise power, the ratio carrier to noise factor is used:

$$\frac{C}{N_0} = \frac{\frac{P_T G_T}{L_{TX} L_T} \frac{1}{L_{FS} L_A} \frac{G_R}{L_{RX} L_R L_{POL}}}{k T_{sys}} \tag{2.16}$$

This value is critical when designing a space communication system. Adding the interference to this equation results in the commonly used signal to interference plus noise ratio:

$$SINR = \frac{1}{\frac{1}{\frac{C}{N_0}} + \frac{1}{CABI} + \frac{1}{CASI} + \frac{1}{CXPI} + \frac{1}{C3IM}} \tag{2.17}$$

2.3 Data Rate

Previous section showed that SINR is a highly valuable metric for satellite operators, as it directly relates the power consumption of the antenna with the design variables of the system. For the end users, however, this value is of low relevance. Satellite communications customers are guided by information trade. Due to the nature of current systems, information is measured in bits, as any knowledge can be easily converted into binary code. The amount of information per time, then, is what determines the capacity of a satellite communication system. This is also known as the data rate and is measured in $\frac{bits}{s}$.

Wave formation: MODCODs

Prior to sending the information into the electromagnetic space, antennas have to convert the electrical signal into a wave. For that purpose, MODCODs schemes are used. MODCOD stands for modulation and coding and is the technique used to encode the information. These schemes are defined by an spectral efficiency and a quality. The spectral efficiency is measured in $\frac{bit}{sHz}$ and represents the amount of information (in bits) that can be transmitted per second with 1 Hz of bandwidth available. The quality determines the minimum amplitude that must be received in order to correctly identify the signal. Thus, the MODCOD scheme acts as a gain or a loss in the link budget equation, which makes the SINR and the MODCOD mutually dependent.

Data Rate equation

MODCODs have a fundamental role in the data rate equation, as it determines the *efficiency* of the codification. The actual amount of information, however, also depends on the bandwidth assigned for the transmission. The equation resulting is very simple and self explanatory:

$$R = \Gamma(P)B \ \left[\frac{bits}{s}\right] \tag{2.18}$$

B is the bandwidth of the channel and Γ stands for the spectral efficiency of the codification ($\frac{bit}{sHz}$), which is directly related with the MODCOD used. As mentioned in the previous subsection, the MODCOD directly depends on the power fed to the antenna for a given SINR. Due to this relation, the data rate depends on the physical characteristics of the system, which makes the solution unique for each set of variables.

Data Rate is the final "product" of space communications. End users contract a specific rate of information in exchange of a revenue for the satellite operator. This contracts are know as Service Level Agreement (SLA) and reign the space communications market. The next chapter will iterate over this concept, as are the fundamental part of any communication.

Chapter 3

Model description

This chapter aims to formulate the problem of this thesis and a general approach to it. To that extent, the space communication scenario will be presented. Section 3.1.1 introduces the variables of the problem, while section 3.1.2 introduces the constrains to that variables. Then, section 3.1.3 discusses the metrics used to assess the problem. Finally, the model used for the simulations will be explained in section 3.2.

3.1 Problem formulation

As seen in chapter 2, a satellite communications process is driven by the necessity to transmit the information from the source point to the demanding point. Although the nature of the demanding point depends on the specific customer, many users have similar behaviour and can be grouped in *types of service*.

Satellite operators, then, have to serve the demand for different types of service using the satellite's resources. The optimal resource allocation is the one that serves all users with the minimum usage of resources. This statement defines the optimization problem. Before solving it, however, we must define the actors involved.

3.1.1 Problem's variables

A communications satellite is responsible of transmitting information from one point to another. For the uplink, a user is understood as the entity that emits this information, while in the downlink is the entity that receives it. For simplicity, during this whole thesis, only the downlink communication will be considered. However, the same formulation and resolution can be applied for the uplink.

At a specific time, a satellite has a defined amount of users that demand certain information. In order to carry out the communication, a satellite has at its disposal a set of antennas, each one with one or more beams. Each beam is assumed to be previously pointed and has a frequency slot predefined. The amount of beams in a satellite will be denoted as N_{beams}. It is also assumed that the conjunction of beams allows to cover all the users. Each user is mapped to one, and only one, beam, which is the responsible to provide the demanded data rate. To do so, the satellite has to allocate power and a bandwidth sub-slot to that user from the pool available.

Following this formulation, each satellite consists of a set of beams and each beam covers a subset of users. In concordance with the electromagnetic formulation and to distinguish the physical receiving antenna from the subset of resources allocated to it, each of the users is assigned a carrier. A carrier is a modulated wave generally used to carry information. Each carrier has two principal parameters: the carrier main frequency and the size of the bandwidth. The former stands for the center and main frequency of the wave, while the latter represents how much bandwidth the wave occupies.

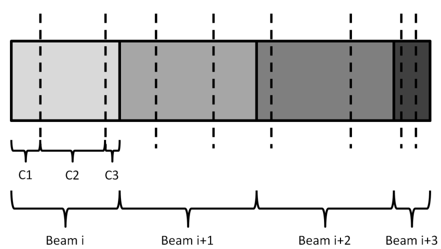


Figure 3.1: Prefixed division of the frequency pool into beams (shades) and variable division of the prefixed slots into 3 carriers (C, dashed lines)

Figure 3.1 shows the distinction between the prefixed frequency split defined by the problem and the variable carrier division modifiable by the algorithm. The bold lines represent the fixed by design frequency slots, while the dashed lines can be moved to adapt user's demand.

The variables of the system, then, are 3 (power level, center frequency and bandwidth used) per carrier. The number of variables grows linearly with the number of users (one carrier per user), which can highly increment the computation time. To avoid this problem, users are divided by type of service (one carrier per type of service). The number of different types of service will be denoted as N_{types}. Now, the number of variables is 3 per number of types of services considered (N_{types}) per number of beams (N_{beams}). To further reduce the complexity, it is assumed that all of the frequency spectrum is to be used. Following this logic and in order to allocate the frequency, the frequency slot for each beam has to be divided into the N_{types}, which can be done with N_{types} - 1 divisions. Then, the final number of variables is:

$$N_{var} = \underbrace{N_{beams} \cdot N_{types}}_{\text{Power allocation}} + \underbrace{N_{beams} \cdot (N_{types} - 1)}_{\text{Frequency allocation}} = N_{beams} \cdot (2N_{types} - 1) \tag{3.1}$$

This number only depends on the number of beams allocated and the types of service considered. Figure 3.2 shows a graphical representation of the resource's variables.

$$\begin{array}{cc} & \text{Type of service} \\ \rotatebox{90}{Beams} & \begin{bmatrix} p_{11} & p_{12} & \dots & p_{1N_{types}} \\ p_{21} & p_{22} & \dots & p_{2N_{types}} \\ \dots & \dots & \dots & \dots \end{bmatrix} \end{array}$$

(a) Power allocation

$$\begin{array}{cc} & \text{Type of service} \\ \rotatebox{90}{Beams} & \begin{bmatrix} b_{11} & b_{12} & \dots & b_{1(N_{types}-1)} \\ b_{21} & b_{22} & \dots & b_{2(N_{types}-1)} \\ \dots & \dots & \dots & \dots \end{bmatrix} \end{array}$$

(b) Bandwidth allocation

Figure 3.2: Graphical representation of resource's variables

3.1.2 Restrictions

Due to the limitations of on-board technology, current satellites have some restrictions regarding its resources. As it is common with modern spacecrafts, the most limiting restriction is the power. Within this restriction, two sub-restrictions must be considered:

- *Total Power*: The total amount of power consumed by all the beams cannot surpass a maximum. This is directly related with the amount of energy that the satellite can absorb and store during time.

$$\sum_b P_b \leq P_{max} \tag{3.2}$$

- *Amplifiers*: For this problem, we assume that the satellite has a maximum number of amplifiers (N_{ampl}) which is less than the number of beams ($N_{ampl} < N_{beams}$). This means that the beams have to be split into the amplifiers, which introduces another constraint regarding subsets of beams and maximum amplifier power: the maximum power for all the beams in the same amplifier cannot surpass the capacity of the amplifier.

$$\sum_b P_{b,a} \leq P_{max,a} \; \forall \; a \; in \; amplifiers \tag{3.3}$$

For the bandwidth allocation, only one restriction has been considered: due to limitation in technology, each carrier has to be allocated a minimum bandwidth. The distance between two consecutive divisions, then, must be higher than a threshold:

$$B_c > B_{threshold} \; \forall \; c \; in \; carriers \tag{3.4}$$

No other restrictions have been considered, as the bandwidth, is not dependent on the satellite's payload.

3.1.3 Metrics: Unmet Demand and Power

To define the metrics, we need to focus on the objective of the system: satisfy the user's demand while minimizing the usage of resources.

- *Required Data Rate ($R_{req,u}$)*: data rate demanded by a user
- *Offered Data Rate ($R_{off,u}$)*: data rate provided by the system to a user

$$R_{off,u} = \Gamma(P_u)B_u \;\forall\; u \textit{ in users} \tag{3.5}$$

- *Met Demand (MD)*: system capacity demanded by the users that the system is able to provide. On the contrary, *Unmet Demand (UD)*, a metric used in previous resource allocations studies [6], is the capacity demanded that the system is **not** able to provide

$$MD = \sum_u min(R_{req,u}, R_{off,u}) \;\forall\; u \textit{ in users} \tag{3.6}$$

$$UD = \sum_u max(R_{req,u} - R_{off,u}, 0) \;\forall\; u \textit{ in users} \tag{3.7}$$

Although both the MD and the UD define how "well" the resources are allocated with respect to the users, the latter is economically more interesting, as usually companies have to compensate users for unmet minimum requirements. Therefore, this will be one of the metrics of our system, and will allow us to compare our results with other algorithms.

Another economically interesting metric is the usage of resources, as the unused resources could potentially lead to serving more users and, thus, more revenues. Within our formulation, we consider two main resources: Power and Bandwidth. While the former directly depends on the payload's capacity, the latter is always available and its limits do not depend on the satellite. Companies are usually more interested in reducing power, rather than reducing bandwidth, and, therefore, the total amount of power consumed will be the second metric of our system.

3.2 Simulation model

Our simulated model contains several classes corresponding to the concepts specified in the section 3.1. The following subsections explain those classes and their main function.

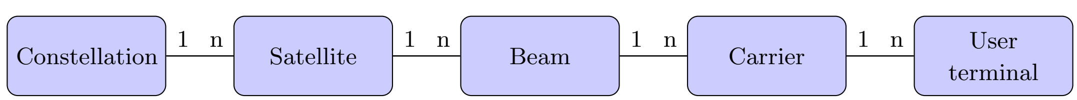


Figure 3.3: Class diagram for the simulated model

3.2.1 User terminal

The User terminal class is mainly a container class useful to store information about the receiving antennas, as those will take part in the link budget computation. Within those parameters, the most relevant are:

- *Location*: useful to assign the user to a beam and the computation of distances for the link budget equation.
- *Type of service*: it determines to which carrier in the beam is going to be assigned.
- *Power*: how much the input signal is going to be amplified. Useful for the link budget equation.
- *Efficiency*: determines a certain loss in the user's antenna. This includes mainly electrical losses, but also depointing and degrading factors.
- *Diameter*: parameter of the antenna to determine the gain.
- *Demand*: capacity that has to be served for that user.

3.2.2 Carrier

Linking class. Contains a list of users assigned to that carrier.

3.2.3 Beam

Linking class. Contains a list of carriers assigned to that beam. It also contains information about the pointing of the beam.

3.2.4 Satellite

Principal class. Contains the list of beams, as well as the satellite's resources and parameters. Within those parameters, the following can be found:

- *Location*: position of the satellite in the space.
- *Power*: for each carrier, how much the signal is going to be amplified. This is one of the modifiable parameters.
- *MODCOD*: for each carrier, which MODCOD is in use. This directly depends on the power per carrier, but also on the other parameters of the computation.
- *Bandwidth*: for each carrier, which sub-slot of frequency is assigned. This is the other modifiable parameter.
- *Efficiency*: determines a certain loss in the satellite's antenna. This includes mainly electrical losses, but also depointing and degrading factors.
- *Diameter*: parameter of the antenna to determine the gain.

- *Beams*: list of beams of the satellite.

With all this information, the following functionalities can be implemented:

- *Get demand*: for each carrier, get the actual demand.

$$R_{req,carrier} = \sum_u R_{req,carrier,u} \; \forall \; u \; in \; users$$

- *Get MODCOD*: for each carrier and given a power, computes the quality of the link and then the MODCOD that is going to be used based on this quality. In the link budget equation, the MODCOD acts as a gain. Thus, knowing the SINR that has to be achieved (this is a parameter set by the operator of the satellite) allows us to compute the MODCOD.

- *Get actual data rate*: for each carrier, get the data rate provided. This functionality assumes that the power and bandwidth are given. As mentioned in 2.3, the spectral efficiency is given by the MODCOD, which depends on the power.

$$R_{off,carrier} = \Gamma(P_{carrier})B_{carrier}$$

This allows us to compute the metrics explained in section 3.1.3 and give a reference on the optimality of the solution found.

3.2.5 Constellation

Linking class. Contains a list of satellites part of the same constellation and a list of terminals. With that information, the assignation of beams to satellites can be done. Although this thesis assumes that each beam is mapped to the nearest satellite, other mappings can be applied without changing the behaviour of the algorithm.

Chapter 4

Metaheuristics approach

The following sections explain the algorithms implemented to solve the problem formulated in section 3.1. First, the reason behind a metaheuristic will be explained. Then, the PSO algorithm will be theoretically presented and the practical implementation will be showed. Finally, this chapter ends with a brief introduction to the GA, which will be used as a baseline to compare to in the results.

Years of research have shown that finding the optimal solution for each of the power and frequency allocation problems is NP-hard and hard to approximate [6] [11]. Therefore, the complexity of the problem scales highly with the number of variables, making the finding of optimal solution infeasible computationally for a sufficiently large number of variables. This backs the reasoning behind a sub-optimal algorithm that allows finding a "good enough" solution in a feasible time.

Several sub-optimal techniques have been developed throughout the years in order to solve optimization problems. One of the most used techniques is what is called the metaheuristic approach. According to Wikipedia, *"a metaheuristic is a* ***higher-level procedure*** *or heuristic designed to find, generate, or select a heuristic (partial search algorithm) that may provide a* ***sufficiently good solution*** *to an* ***optimization problem****, especially with incomplete or imperfect information or* ***limited computation capacity****"* [19]. This definition fits perfectly the type of problem described previously and, thus, it is a reasonable strategy to approach the problem. Moreover, some metaheuristics have already been successfully applied to the power allocation, frequency assignment and joint problem [9, 6, 17].

4.1 Particle Swarm Optimization: PSO

The Particle Swarm Optimization (PSO) is a metaheuristic algorithm, first presented in [20], based on the movement of bird flocks. In nature, bird flocks try to find the best place to land by flying over the search space and analyzing the possible landing spots. The flight is directed by a leader, whose movements determine the direction of the flight. Each bird also remembers the best place found so far. By analyzing a sufficient portion of the search space over time, flocks are able to find a *good enough* landing spot. The PSO algorithm is constructed around all these ideas.

4.1.1 Flight

Analogising bird flocks, PSO algorithms are based on a set of "*birds*" flying through the search space aiming to find the best solution. These birds are just entities able to identify solutions and move through the space. As any movement, the flight is mainly characterized by a position and speed. A position in the search space is equivalent to a solution and the PSO's objective is to find the best position. Therefore, these elements are broadly called *particles* due to the resemblance with their physical analogy. The nature of the set of particles classifies the PSO as a population-based algorithm.

The particles use the concepts of *leader* and *memory* to define their trajectory. The leader is associated with the *global best*, which is the best particle of the set of particles. This underlies that all the particles know the position of all the other particles in the set and move towards the best one. This is usually a behaviour found in hives or *swarms*, which is the reasoning behind the usage of the latter term for a set of particles in PSO. The memory is associated with the *local best*, which is the best position that that particle has found throughout time.

With this information, the particle decides its direction and speed at every time step. If the time is discretized, the equations to represent this double pull can be very simple to represent:

$$v(t) = v(t-1) + [g - x(t-1)] + [l - x(t-1)] \tag{1}$$

$$x(t) = v(t) + x(t-1) \tag{2}$$

Where g is the position of the best particle of the swarm, l is the best position visited by the particle and x, v are the position, speed, respectively, of the particle. The movement is a lineal combination of the pulls towards the global and local bests and the previous speed. In order to control the algorithm behaviour and to allow exploration capacity, each of the pulls is multiplied by influence factor and a random value. The equation 1, then, becomes:

$$v(t) = v(t-1) + gf * rand() * [g - x(t-1)] + lf * rand() * [l - x(t-1)] \tag{3}$$

Where gf is the global influence factor that determines the strength of the pull towards the global best, lf is the local influence factor, and rand() is a random value in the interval [0, 1).

Following the introduction of the PSO in [20], one of the authors presented another work with an additional parameter, called the inertia weight [21]. This parameter is widely used in PSO applications and allows for a better convergence towards the optimum. It basically controls the speed when the pull is zero, acting as a break. Introducing this new parameter to the equation:

$$v(t) = w * v(t-1) + gf * rand() * [g - x(t-1)] + lf * rand() * [l - x(t-1)] \tag{4}$$

Where w is the inertia weight (usually $w \in (0, 1]$ for a *break* behaviour).

4.1.2 Global and local bests

The previous section showed that, in order to implement a PSO algorithm for a given application, it is necessary to define the concepts of global best and local best. Both parameters are simple to apply to single objective optimization problems: the 'best' solution is the one that gives less fitness (minimum optimization). Multiple objective problems, which is the case of our formulation, have more than one fitness, so the definition is not usable anymore. Work [22] shows a useful way to deal with this problem. This work uses the concepts of Pareto Front and dominance to find the best particles of the search.

The Pareto Front (PF) concept appears when a decision has multiple ways to rate the considered options. That is, in order to assess the fitness or wellness of an option, several different independent ratings can be used. Buying a car, for example, implies a trade-off between price and quality. Cheapest products usually have less quality, while more expensive products tend to perform better. Trying to optimize both quality and price will give us a list of products, each one with a different trade-off. At this point, the concept of dominance enters the game. Between two options, one dominates another if it is at least equal in N-1 dimensions and better in one. Following the example, a product with more quality and less prize will always be preferable (not having anything else into account). The Pareto-Front is then the list of non-dominated solutions available.

Our formulation, as stated, depends on two metrics, UD and Power, which convert the problem into a multiple objective problem. Instead of having a single 'best' solution, we have a Pareto Front of solutions with a different UD - Power trade-off. For the equations, however, we need just one leader to follow. Thus, we have to pick one of the particles in the Front. Work [22] suggests to divide the n-dimensional fitness space into hyper-volumes, assign a fitness to each volume based on the crowding of each hyper-volume and use a wheel selection [23] to prioritize the emptier volumes. The wheel selection technique is based on assigning to each of the options a probability and randomizing the selection based on this probability. This technique is useful for equally important metrics, where the diversity of solutions has to be preserved. In our case, clearly, the UD metric is economically more important than power, as the financial benefits of serving more users are extremely high. Therefore, we assign a probability based on the UD metric. The wheel selection algorithm, then, chooses a leader between the Pareto Front particles, prioritizing the low UD region, but allowing diversity to avoid fast convergence to local optima. Using this technique, each particle chooses its own leader.

Regarding the local best, the computation is more simple, as only two points have to be taken into account: the best point remembered and the current point. The concept of dominance is used at this point: if any of the points dominates the other one, the non-dominated point is chosen. In any other case, pick randomly one of the points. While this is the approach suggested in [22], for our non equally important metrics, always the less UD demand point is chosen. This simple selection is not useful when choosing the global best due to the higher number of possible selections.

This definitions allow us to determine the best global and local in order to apply the flying equations to the particles.

4.1.3 Implementation

General Algorithm

Once the overall functioning of the PSO has been explained, the implementation must be presented.

Algorithm 1 shows the main body of the PSO algorithm. It is based on the concepts already explained in previous sections. Each function, however, will be detailed in the following sections.

Algorithm 1 Main PSO

```
procedure PSO
    swarm ← InitializeParticles(num_particles)
    for each particle in swarm do
        PostFlight(swarm)
    for all generations do
        for each particle in swarm do
            leader ← SelectBestParticle(swarm)
            Flight(particle, leader)
            Mutation(particle)
            PostFlight(particle)
procedure PostFlight(particle)
    CheckRestrictionsAndRepairParticle(particle)
    ComputeFitness(particle)
    UpdateBestLocal(particle)
```

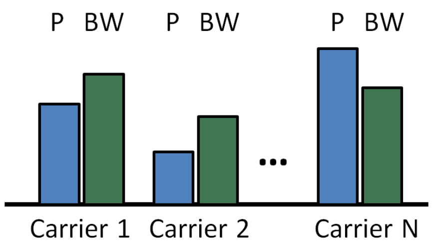
InitializeParticles

The first step in any population-based algorithm is initialize the current individuals (particles for PSO). For our formulation, power and bandwidth as explained in section 3.1.1 must be initialized, as well as initial speeds and best local memory.

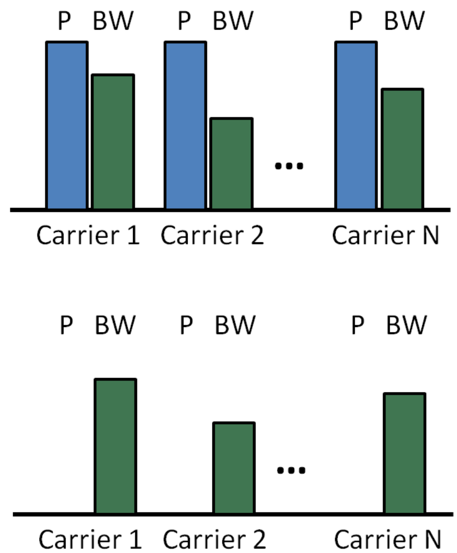
Figure 4.1a represents graphically the concept of a particle position:

Based on experimental data, the PSO algorithms usually work best when the optimal solution lies within the current search space, as their exploration capabilities is low compared to other algorithms. This means that the initialization has a big role on how the algorithm will perform. From the two variables to initialize, the one that most directly affects the metrics is the power. In order to cover as much space search as possible, some part of the population will be initialized with 0 power, while the other will be initialized to maximum. This allows a big search space and a easier optimal finding for the algorithm. As the all the bandwidth is always used, it's direct impact is lower and, thus, it will be initialized randomly.

The speed (v)is also an important initialization factor. As we have set the limits of power in the initialization, we let the algorithm decide the speed and, therefore, we initialize the speed to 0.



(a) Definition of a particle's position



(b) Two types of initialization: to maximum power (upper) and to minimum power (lower). BW is randomized for both cases

Figure 4.1: Particle's position and initialization

As expected, the current local best position is the current position. The global best will be immediately chosen based on the best initialized particle.

SelectBestParticle and UpdateBestLocal

The algorithm for the selection of the best global particle and the best local position is referenced previously in this section (*Global and local bests*). For the global best, a register of the current Pareto Front combined with the wheel selection technique is used, while the information of the local best is stored in the particle itself. It is noticeable that each particle has its own leader that guides the current iteration. By doing so, we allow the algorithm to rely on several particles, instead of just one, which could lead to a unexpected early bad convergence.

Flight

The flying of a particle is determined by equations 2 and 4. The leader and memory are already established at this point of the iteration. The random values are computed at every iteration, which makes the algorithm have different behaviour at every run, even with the same initialization. This will be important when analyzing the results, as several runs may lead to different solutions.

CheckRestrictionsAndRepairParticle

This function refers to the restriction explained in section 3.1.2. Before computing the new fitness, the correctness of the current state must be validated. If the position is not valid, it has to be repaired. In our approach, we consider the following non-valid rules:

- *Out of limits* (Equation 3.2): the position is above the maximum or below the minimum power or bandwidth. In the formulation, it can be seen that the power is limited by the satellite, being 0 the minimum and the maximum amplifier capacity the maximum. The bandwidth is just a slot that has to be subdivided, while the variables are the position of the subdivision. By normalizing, the bandwidth can be clamped to the [0, 1] interval.
- *Amplifier* (Equation 3.3): for each amplifier, the maximum capacity cannot be surpassed. If that's the case, all the carrier's powers within that amplifier are reduced proportionally until the maximum is reached.
- *Bandwidth minimum distance* (Equation 3.4): due to the limitations in current technology, even if the demand is 0, some resources have to be assigned to the carrier to maintain the connection. Therefore, a sub bandwidth slot of 0 is not possible. If that's the case, we reduce the neighboring slots to allow a minimum bandwidth for every carrier.

ComputeFitness

Using the class and function explained in section 3.2.4, both the metrics of the particle can be easily computed. The particles can then be rated and the Pareto Front can easily be found.

Mutation

Although it is not broadly used in PSO applications, our implementation includes a particle mutation [24]. This type of function allows for a better exploration, as allow the particles to get out of the current exploration zone. In our case, the mutation function simply changes some of the positions randomly, aiming for a broader search.

4.1.4 Heuristics

Until this point, almost no information about the problem has been used in the implementation of the algorithm. In order to improve the performance of the PSO, some directives can be implemented to help reduce the search space and decrease convergence runtime.

From the problem, it is known that, for a specific carrier, a decrease in power or bandwidth implies a decrease in data rate. As the UD directly depends on this factor, a decrease in data rate may imply an increase in UD. Therefore, in order to achieve higher data rates, we have to increase the resources allocated for that carrier. This can be used in the flight function to *guide* the flight. In our implementation, if a specific carrier has some UD, we do not allow to decrease the power nor bandwidth. This directly means that the speed of the variables related to that carrier cannot allow the decrease in resources. On the other hand, if the UD is zero, the resources may be excessively allocated. Then we don't allow allocating more resources for that carrier. This implementation favors the reduction of both metrics, putting more emphasis in the UD, which is of higher relevance.

4.1.5 Parameter selection

Once the algorithm's functions have been defined, the different parameters that control the behaviour must be decided:

- *Global Influence Factor (gf)*: As suggested by the original PSO implementation [20], this factor has a value of 2. The reasoning behind this number is the equiprobability of not arriving to the point and surpassing the point, allowing some exploration capabilities.
- *Local Influence Factor (lf)*: For the same reasons behind the gf, this factor has a value of 2. Also, neither the global best nor the local best should be prioritized in front of the other. Thus, both influence factors should be kept equal.
- *Inertia Weight (w)*: This factor has been assigned a value of 0.729844 after the comparison made in [25], which states this value as the best convergence value.
- *Maximum speed*: In order to allow some degree of exploration, we clamp the maximum speed of the algorithm to certain limits. By doing so, we avoid getting stuck in the initialization values, and enforce a minimum exploration before convergence. For power, the limit is set to 2.5% of the maximum power, for bandwidth, the limit is set to 5% of the maximum bandwidth.
- *Mutation probability*: This states the probability of a single variable of mutating. For our implementation, we have set this value to 0.0625% allowing the change of only a few variables every iteration.

4.2 Genetic Algorithm: GA

This section is intended to give a brief description of the GA and its application to this problem. As the GA is not the main topic of this thesis, just the general concepts will be explained.

The Genetic Algorithm (GA), also known as Evolutionary Algorithm, is a metaheuristic, population-based algorithm built around the evolution of living populations. Throughout time, populations suffer from different effects that lead to better and stronger individuals, able to better fit in the current environment. The GA uses those functions to evolve the set of solutions and improve them towards the global optimum.

Within those functions, three are commonly found:

- *Selection*: The population only supports a maximum number of individuals. Thus, creating new individuals imply that some part of the population will be erased in order to leave place to the new generation. Due to the multiple objectives, the Pareto Front and dominance concepts reappear at this point.
- *Mating*: Following the reasoning behind animal population, the way to create new individuals is based on the mating within the current population: two individuals create another by crossing its characteristics. The new individual has characteristics from both creators.
- *Mutation*: Individuals can also create another individual by randomly mutating some of its characteristics.

In the algorithm, the mating and mutating functions allow the population to evolve, while the selection ensures the convergence to the best solutions (a.k.a. global optimum).

The implementation of the Genetic Algorithm in this thesis is a similar approach as the presented in [17]. To this algorithm, the heuristic presented in section 4.1.4 has been added.

Chapter 5

Results

This chapter aims to present the results obtained with the explained algorithms. First, the simulation data will be described. Then, the results for several scenarios will be provided and discussed.

5.1 Traffic model

All the analysis in this thesis are based on the traffic model provided by SES S.A., which represents a distribution of beams across America. This model contains information about a set of beams, including position, user's antenna characteristics, maximum demand (SLA),... It contains all the necessary physical characteristics to compute the link budget equation. A part from this spatial model, it also includes a temporal model, with the demand per type of service every 5 minutes for a 24h period.

The set contains 160 beams, distributed along America within ±65^{o} latitude. With this distribution, we consider several demand cases based on the number of type of services considered. At maximum, the model considers 4 different types of services, which will be referred as A, B, C and D. In terms of demand, A<B<C<D. Considering the demand in each beam, taking 1 or 2 types (e.g. A or AB) can be stated as *low demand*, where the user's requirements are always met and the UD is zero. Taking 3 types (e.g. ABC) is stated as *balanced demand*, where the user's requirements are vastly met and the UD is near zero. Finally, *excess demand* is understood as taking all 4 of the types (e.g. ABCD) and the requirements are not met. The algorithms try to minimize UD, but never reaches 0.

Each beam has its own prefixed frequency slot defined by the model. The frequency slot distribution tries to minimize the interference between the beams. As it is constrained by the model, the algorithm cannot change this distribution. The carriers, however, receive a sub-slot of the bandwidth assigned to the beam and that is one of the variables considered in the problem and changeable by the algorithm.

5.2 Simulation parameters

This section presents the values of the parameters chosen for each algorithm.

Parameter	Value
Swarm size	500
Global factor	2
Local factor	2
Power max speed	2.5%
Bandwidth max speed	5%
Mutation probability	15%
Variables mutated	1/16%

(a) PSO parameter selection

Parameter	Value
Population size	100
Crossing probability	75%
Gens crossed	60%
Alpha blending (crossing)	20%
Mutation probability	15%
Gens mutated	2%

(b) GA parameter selection

Table 5.1: PSO and GA parameter selection

5.3 Scenario 1: Power allocation

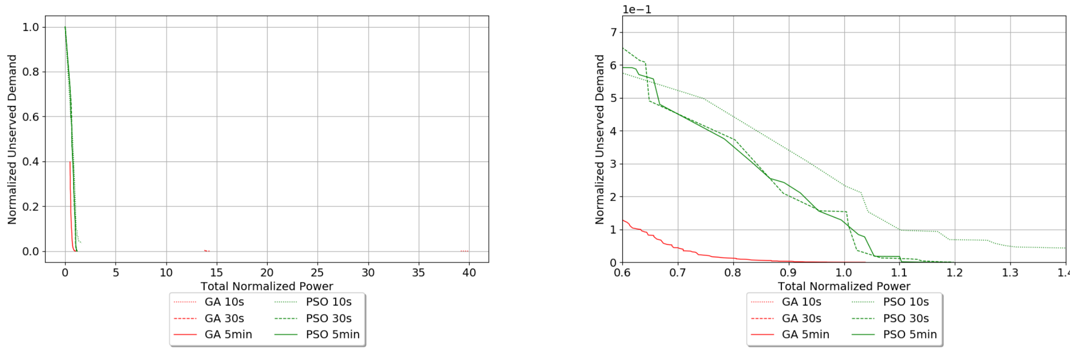
This first scenario presents a basic concept test of the algorithms and a general overview of their performance in the described problem. In order to assess the performance of the algorithms, only the power will be allocated, and the bandwidth will split among the carriers based on the user's maximum contracted demand, as for this case an optimal power allocation can be found. Both the PSO and the GA will be compared with this baseline. For the results, the power will be normalized to the optimal power, while the UD will be normalized to the total demand.

The test will be constituted of three sub-scenarios: low, balanced and excess demand (types of service: A, ABC and ABCD). For all three cases, the test will be run for a single timestamp. The algorithms will be restricted to 5 minutes in order to accommodate the parameter's change rate imposed by the technology restrictions. Each algorithm will be run 4 times for each case. The results will be shown for the closest to average solution. To analyze the convergence of the algorithms, the results after 10, 30 and 300 seconds will be showed. Each one of them correspond to a different run.

5.3.1 Sub-scenario 1: Low demand

This sub-scenario presents the results in case of low demand (type of services: A). Under this conditions, all the demand is met and the algorithms only have to try to minimize power ($UD = 0$).

Figure 5.1 presents the PF in the low demand scenario for both the PSO and the GA. The results in the table clearly show the behaviour of both algorithms: the PSO reaches a solution



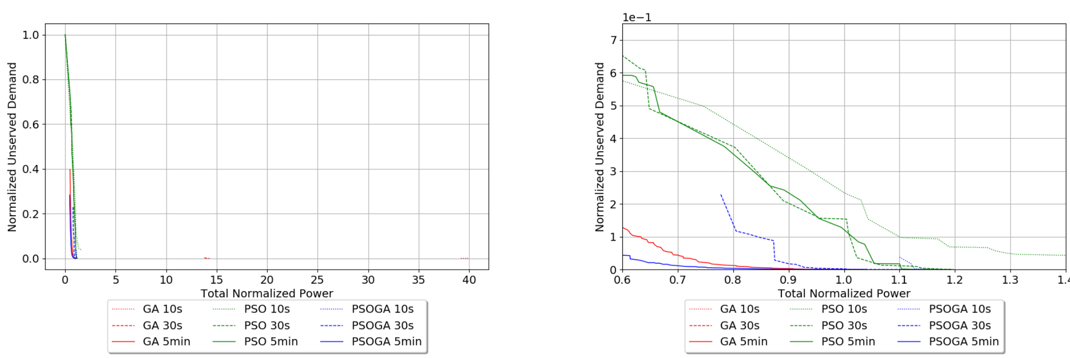
(a) Original

(b) Zoomed

Figure 5.1: Scenario 1, Pareto Front for Low demand

comparable to the optimal very fast (30s to be 20% above the optimal power), but it gets stuck in a local optima. On the other hand, the GA starts very slowly, having 40 times the optimal power at the 10s mark. In the long term run, however, the algorithm gets closer to the global optimum, improving the result of the PSO. The GA is asymptotically optimal.

In this implementation, the PSO behaves similarly to a simulated annealing (SA): both algorithms are very fast but have a strong pull towards local optimas. Similarly to [6], which suggests a hybrid implementation using SA-GA for power allocation, I propose a hybrid PSO-GA, which benefits from the rapid start of the PSO and the better long term performance of the GA. This hybrid will, from now on, be added in the results, and its exact implementation can be seen in appendix A.



(a) Original

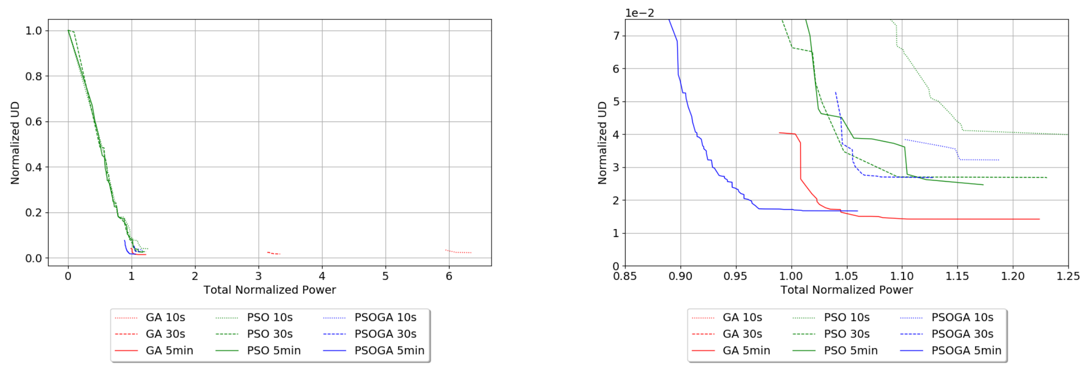
(b) Zoomed

Figure 5.2: Scenario 1, Pareto Front for Low demand, including the hybrid

Figure 5.2 presents the PF in the low demand scenario for the PSO, GA and the hybrid PSO-GA. As can be seen, the hybrid already outperforms the PSO in the 10s mark (as the GA has already started) and improves the optimality of the GA in the long term run.

5.3.2 Sub-scenario 2: Balanced demand

This sub-scenario presents the results in case of balanced demand (type of services: ABC). Under this conditions, the demand is vastly met and the algorithms have to aim for $UD = 0$.



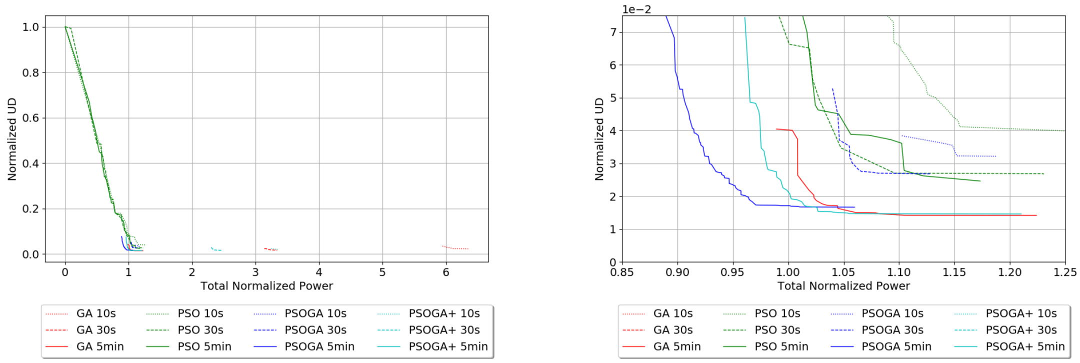
(a) Original (b) Zoomed

Figure 5.3: Scenario 1, Pareto Front for Balanced demand

Figure 5.3 shows a similar behaviour as the previous scenario for both the PSO and the GA: while the PSO converges faster, the GA outperforms the PSO in the long run. Under this conditions, the PSO is not able to find a clear trade-off between power and UD. This is shown in the concave form of the PF. On the other hand, the GA and hybrid do find this trade-off, leading to a convex PF. In this scenario, however, the hybrid is not able to improve the results of the GA, getting stuck in the PSO's local optima. Although the hybrid reaches lower powers, the minimum UD reached by the GA is slightly lower.

The reasoning behind this behaviour lies in the initialization of the algorithms: the PSO works best when there exists an optimal solution ($UD = 0$) and this solution is within the search space. The GA, on the other hand, performs better when the population has higher power than the optimal (right in the graphs), as then the algorithm can focus on reduce power without affecting the UD. These two characteristics collide in the hybrid.

In order to improve the performance of the hybrid, a second version of the PSOGA (called *PSOGA+*) has been developed. In this version, when the population is transferred from the PSO to the GA, the power is multiplied by a random factor between 2 and 4. By doing so, we give the GA a wider search space with lower UD, leading to a better performance. It is notable that this version of the hybrid only outperforms the other version when the UD cannot reach zero, as for this case the PSO reaches a local optima and constricts the search space of the GA.



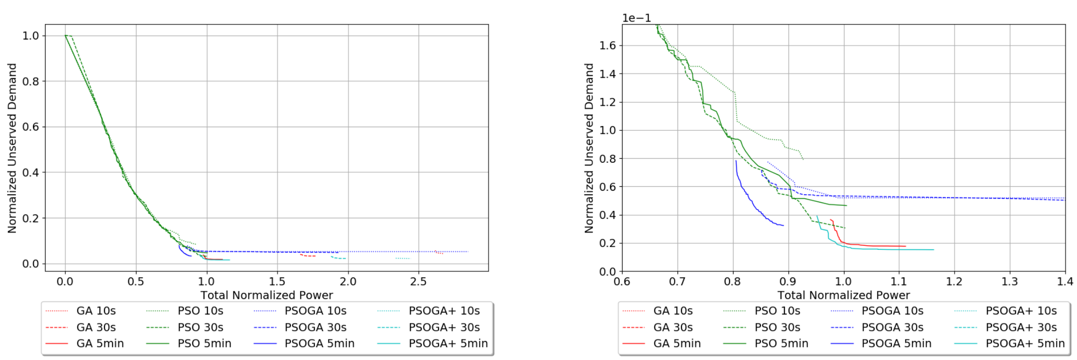
(a) Original (b) Zoomed

Figure 5.4: Scenario 1, Pareto Front for Balanced demand, including the PSOGA+

It can be seen in figure 5.4 that the PSOGA+ reaches an UD comparable to the GA, while reducing the power. For higher UD, however, version 1 of the hybrid outperforms version 2, as the initialization proposed inherently increases power.

5.3.3 Sub-scenario 3: Excess demand

This sub-scenario presents the results in case of excess demand (type of services: ABCD). Under this conditions, the demand is vastly met, but $UD = 0$ is unreachable, so the algorithms must try to reduce it as much as possible.



(a) Original (b) Zoomed

Figure 5.5: Scenario 1, Pareto Front for Excess demand

Figure 5.5 presents again the same behaviour for the PSO and the GA. In this scenario, however, both hybrids perform a bit different as for the balanced case. The PSOGA finds a search space with much higher UD than the GA, but with much lower power. The solutions found are complementary to the ones found in the GA, but, as we are more interested in the low UD zone, we can state that the GA clearly performs better un the case of excess demand than the hybrid. The PSOGA+, on the other hand, outperfoms the GA in the same search space, finding an improved PF in the same time. For the cases of excess demand, the PSOGA+ outperforms all the other algorithms.

5.4 Scenario 2: Optimizing power and bandwidth

This scenario constitutes the core comparison of this thesis. For this case, joint power and bandwidth will be allocated. The four algorithms described (PSO, GA, PSOGA and PSOGA+) will be compared between them, as the optimal solution cannot longer be found.

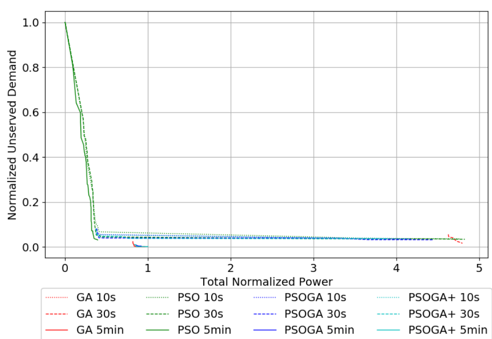
As the previous scenario, the test will be composed of three sub-scenarios: Low, Balanced and Excess demand (AB, ABC and ABCD types of services respectively). For all three cases, the test will be run for three different timestamps: night, morning and late afternoon. Only the most representative timestamp will be showed in this section. The complete results can be seen in appendix B. The algorithms will be restricted to 5 minutes in order to accommodate the parameter's change rate imposed by the technology restrictions. Each algorithm will be run 4 times for each case. The results will be shown for the closest to average solution. To analyze the convergence of the algorithms, the results after 10, 30 and 300 seconds will be showed.

As for scenario in 5.3, the PSOGA+ will be based on a power multiplication, while bandwidth will remain unchanged.

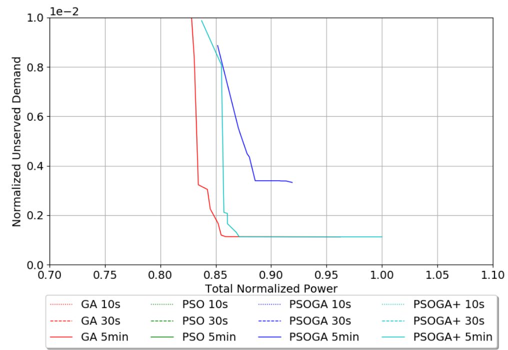
5.4.1 Sub-scenario 1: Low demand

This sub-scenario presents the results in case of low demand (type of services: AB). Under this conditions, all the demand is met and the algorithms only have to try to minimize power ($UD = 0$). Figure 5.6 presents the PF in the low demand scenario for the four algorithms in the 18h timestamp. The results have been normalized to the power at lowest UD and total demand respectively. The general behaviour of the GA and PSO can be observed once again in this results: the PSO (green lines) rapidly reaches the low power area at the expense of UD. The GA (red lines) starts slowly but end up converging to a lower UD after 5 minutes. Regarding the hybrids, the PSOGA (blue lines) is unable to outperform the GA despite the PSO initial boost, while the PSOGA+ (cyan lines) reaches the same UD as the GA but with higher power..

In conclusion, for low demand scenarios, the PSO and its hybrids are able to provide a low power - high UD solution very fast (10s), but are outperformed by the GA in a long term run. The explanation behind this behaviour is the strong pull of the PSO and derived algorithms towards local optimas, which restrict the exploration capabilities of following algorithms.



(a) Original



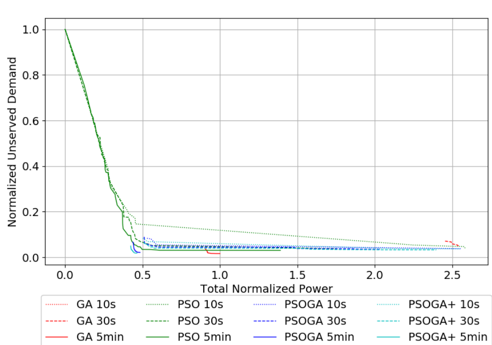
(b) Zoomed

Figure 5.6: Scenario 2, 18h timestamp, Pareto Front for Low demand

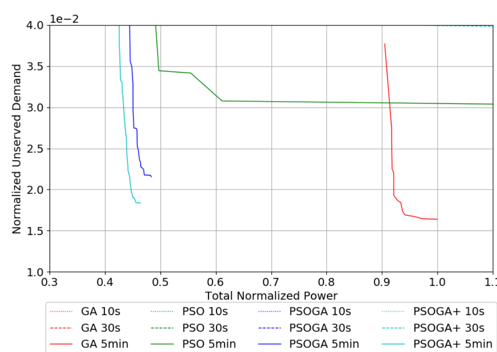
For this thesis, a restriction in time of 5 minutes has been assumed. In case that the real scenario imposes a more restrictive constraint (e.g. 2 min), the hybrid PSOGA+ would outperform the other algorithms.

5.4.2 Sub-scenario 2: Balanced demand

This sub-scenario presents the results in case of balanced demand (type of services: ABC). Under this conditions, the demand is vastly met and the algorithms have to try to reach $UD = 0$. Figure



(a) Original



(b) Zoomed

Figure 5.7: Scenario 2, 0h timestamp, Pareto Front for Balanced demand

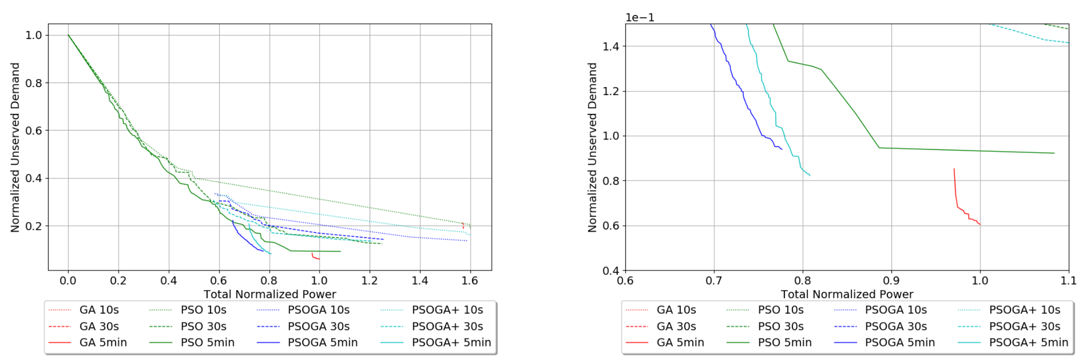
5.7 presents the PF in the balanced demand scenario for the four algorithms in the 0h timestamp. The differences in search space between the GA and the PSO are clear. While the GA aims for low

UD, giving less importance to power, the PSO prioritizes both metrics equally, reaching far lower power solutions, but higeher UD. The solutions found by both algorithms are complementary. The hybrids try to overcome this difference in the search space gap, clearly outperforming the PSO. They are unable, however to beat the GA in the low UD region. Moreover, the PSOGA+ clearly outperforms the PSOGA in this scenario. The initial increase in power helps the algorithm to find lower UD, while the power is not affected in the long term run.

In the final iteration, the PSOGA+ finds a solution with 50% lower power than the GA and 20% higher UD. In the global perspective, however, the solution found by the PSOGA+ reaches a 0.19% of UD, while the GA reached 0.16%. If the satellite operator has a 5 minutes restriction, it should decide, then, if the costs of this lower power could compensate the higher UD. In case the restriction implies a lower time, the election would clearly move towards the PSOGA+.

5.4.3 Sub-scenario 3: Excess demand

This sub-scenario presents the results in case of excess demand (type of services: ABCD). Under this conditions, the demand is never met and the algorithms have to try to minimize UD.



(a) Original (b) Zoomed

Figure 5.8: Scenario 2, 9h timestamp, Pareto Front for Excess demand

Figure 5.8 presents the PF in the excess demand scenario for the four algorithms at the 9h timestamp. The differences in search space between the GA and the PSO are remarked once again. As in all the previous sub-scenarios, the GA is consistently able to reach the low UD zone, while the PSO gets stuck in local optimas. Regarding the hybrids, the PSOGA is not able to improve the UD found by the PSO, but reaches lower power. On the other hand, the PSOGA+ exchanges some of this power improvements to get lower UD. This lower UD, however, is not comparable to the one found by the GA (50% higher in the last iteration).

Once again, the solutions of the algorithms are complementary due to the differences in the search space. If we give a higher value to the low UD zone, however, the GA clearly outperforms all the other algorithms, including the hybrids, in the long term run.

Chapter 6

Conclusions

This chapter summarizes the main findings of this thesis and introduces possible future works to improve the results presented in this document.

6.1 Conclusions and remarks

This thesis presents a PSO and two hybrids PSOGA implementations to solve the RA problem in satellite communications. First, the motivation and objectives of this work have been presented. Second, the satellite communications context has been introduced. Third, the problem has been formulated and the simulation model has been explained. Fourth, the implementation of the PSO has been shown and, finally, the results for the PSO, the baseline GA and the hybrids have been discussed.

As a first remark, the PSO is a suitable algorithm to solve the dynamic resource management problem in High-Throughput Multi-beam satellite systems and can be successfully implemented in a real-case application.

For power and joint power and bandwidth allocation, the PSO has a very fast convergence (15 to 20 iterations, 12 - 15s for 500 particles) towards a local optima. The results show big improvements in early stages with respect to a standard implementation of a GA. The latter, however, consistently outperforms the PSO in the long term run.

Both the characteristics of the PSO and the GA can be unified in a hybrid PSOGA. The PSOGA and variants clearly outperform both the PSO and the GA in the problem of power allocation, reaching lower UD regions.

For the joint power and bandwidth allocation problems, the hybrid algorithms are able to reduce highly (up to 50%) the power consumption, at the expense of an up to 50% increase in UD in the worst case, compared with the sole GA execution in the 5 min mark. In a 30s execution, however, the PSO and hybrids reach an 80% power reduction, while achieving 2% lower UD, clearly outperforming the GA.

6.2 Future work

This thesis has introduced the formulation and implementation of the Particle Swarm Optimization method to the joint power and bandwidth allocation subproblem inside the Dynamic Resource Management problem for satellite communications. Possible extensions of the work presented in this thesis may cover:

- Inclusion of the frequencies flexibilities for modern constellations: while this thesis works under a frequency fixed model, modern constellations allow to change the frequency per beam, variable that could potentially be included in the algorithm as a decision variable.
- Inclusion of other subproblems inside the RA problem: this thesis presents the implementation of the joint power and bandwidth allocation problem. Other subproblems inside the RA, such as the beam placement and beam shape could also be included in the decision variables of the algorithm.
- PSO and hybrids heuristic improvements: while this thesis works with the presented implementation of the algorithms, further improvements in the algorithms could reach significant better results.
- Robustness and size sensitivity analyses: to further understand the behaviour and advantages of all algorithms.
- Parameter tuning: while for this thesis, the parameter selection has followed an ad hoc procedure based on the results obtained, a further work could include a better parameter refining to increase the performance of the PSO and hybrids.

Appendices

Appendix A

PSO-GA: a hybrid approach

In general terms, the PSO is a fast optimization technique with low exploration capabilities. This tends to lead the algorithm to a local optima solution. On the other hand, the GA is a slower convergence technique with high exploration and exploitation capabilities. This leads to a global optimum at the cost of computation time. These characteristics suggest for a hybrid algorithm, able to combine the fastness of the PSO and the exploration of the GA to converge faster to the global optimum.

A.1 Implementation of a PSO-GA

We envision this hybrid as a two step process: first, a fast PSO execution to obtain a better starting point for the GA and then a long GA run to reach the expected convergence of the algorithm. Based on this, our implementation is based on a 10-iteration PSO run followed by the GA. The explanation of this *10-iteration* concept is detailed in the following lines.

Figure A.1 shows the PSO fast convergence. In very few iterations, the algorithm provides a *good enough* solution. This value, however, is a local optima, and the algorithm gets stuck in there. For this reason, the starting point of the GA should not be the convergence value of the PSO, but rather a previous step, before entering the local optima. The 10th iteration is a good compromise between a far from optimal solution and a local optima solution.

Although the transfer of population between the two algorithms is simple due to the nature of the implementations, the search space has to be taken into account. In our formulation, the UD is more important than the power consumed. While both metrics are interesting from the point of view of the algorithm, the low power - high UD region is not interesting from the financial point of view. Thus, the interest region will be around the low UD region. While the PSO has not trouble when dealing with a big search space, the exploitation capabilities of the GA make the algorithm perform better in an enclosed small region. Therefore, when transfering from the PSO to the GA,

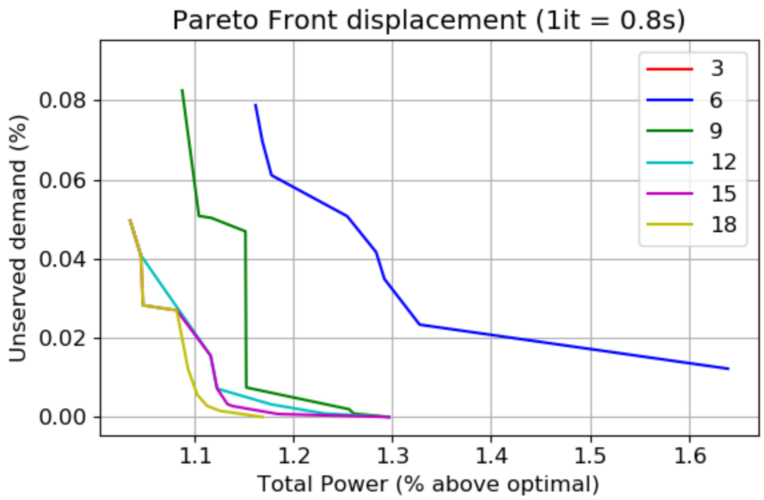


Figure A.1: Particle swarm optimization convergence in 18 iterations

our implementation only gives the low UD population, while ignoring the other individuals, to optimize the performance of both algorithms.

A.2 PSOGA+

While the idea of a hybrid PSOGA was to use the fast start of the PSO while avoiding local optimas, this is hard to do in practice. The pulling towards PSO convergence values remains during the whole execution, leading the hybrid to worst results than the sole GA run. To further avoid this local optimas, I developed a modified version of the algorithm. This new hybrids, called PSOGA+ has the same run characteristics as the PSOGA, with the only difference being the population transfer. Within this transfer, each of the powers of the particles in the swarm is individually multiplied by a random factor between 2 and 4. This allows the execution to move away from the local optimas while maintaining a sufficiently low UD found by the PSO. This random factor will be denoted as population modification factor or PMF.

A.3 Simulation parameters

This section presents the values of the parameters chosen for both the PSOGA and the PSOGA+.

Parameter	Value
Iterations	10
Swarm size	500
Global factor	2
Local factor	2
Power max speed	2.5%
Bandwidth max speed	5%
Mutation probability	15%
Variables mutated	1/16%
PMF (PSOGA+)	2-4

(a) PSO parameter selection

Parameter	Value
Population size	100
Crossing probability	75%
Gens crossed	60%
Alpha blending (crossing)	20%
Mutation probability	15%
Gens mutated	2%

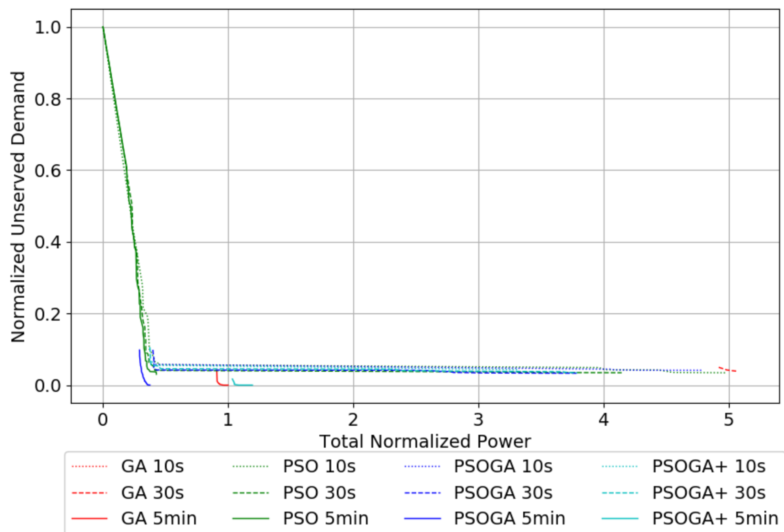
(b) GA parameter selection

Table A.1: PSOGA and PSOGA+ parameter selection

Appendix B

Scenario 2 complete results

This chapter presents the complete results for joint power and bandwidth allocation with the four algorithms presented.



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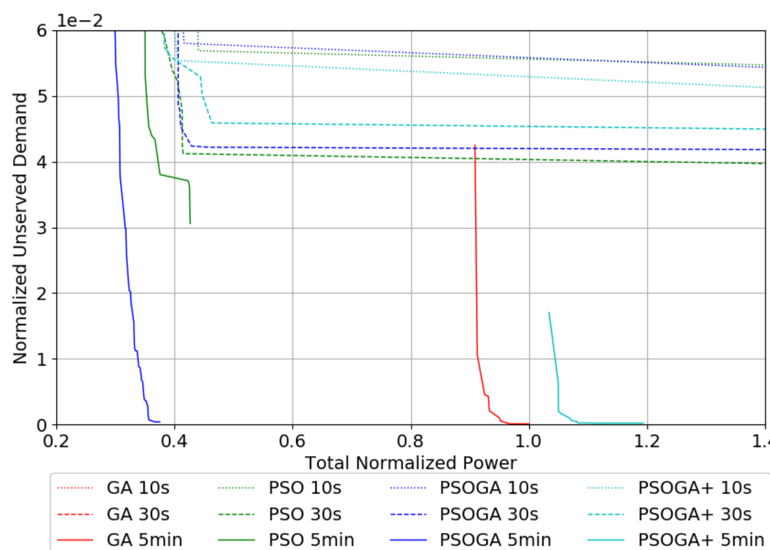
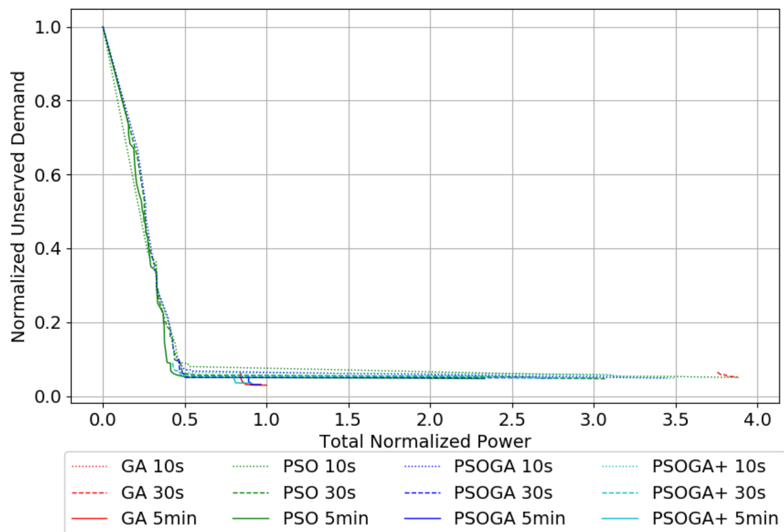
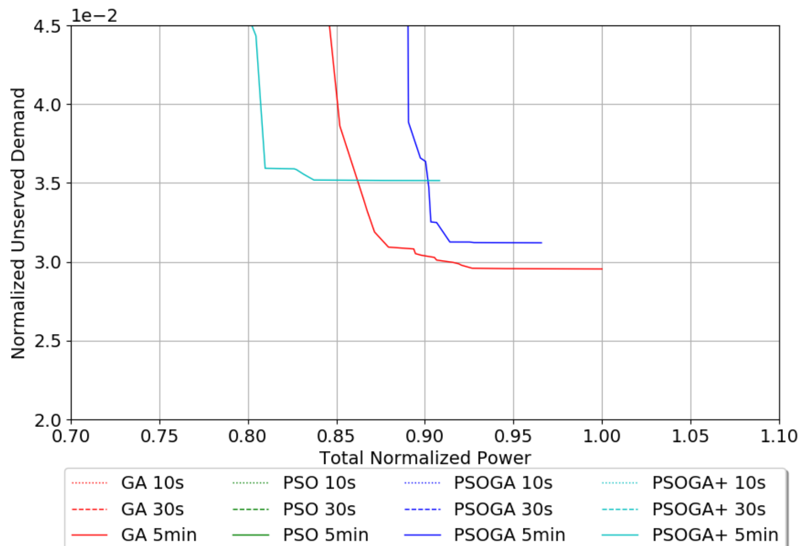


(b) Zoomed

Figure B.1: Scenario 2, 0h timestamp, Pareto Front for Low demand

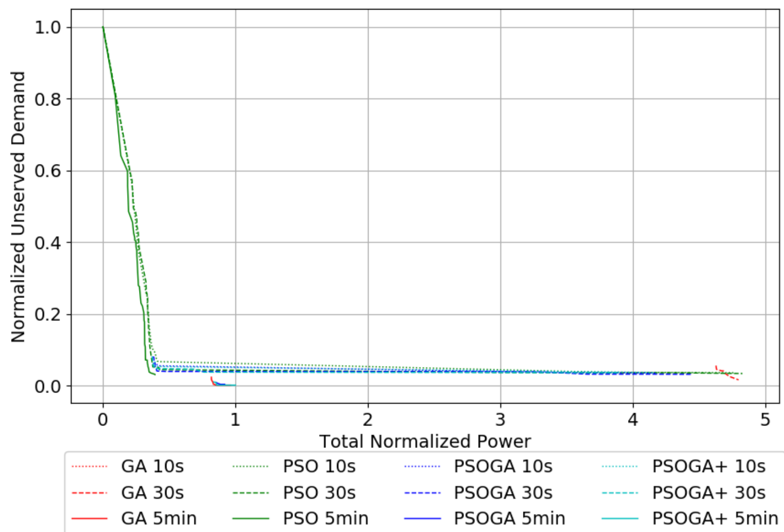


(a) Original

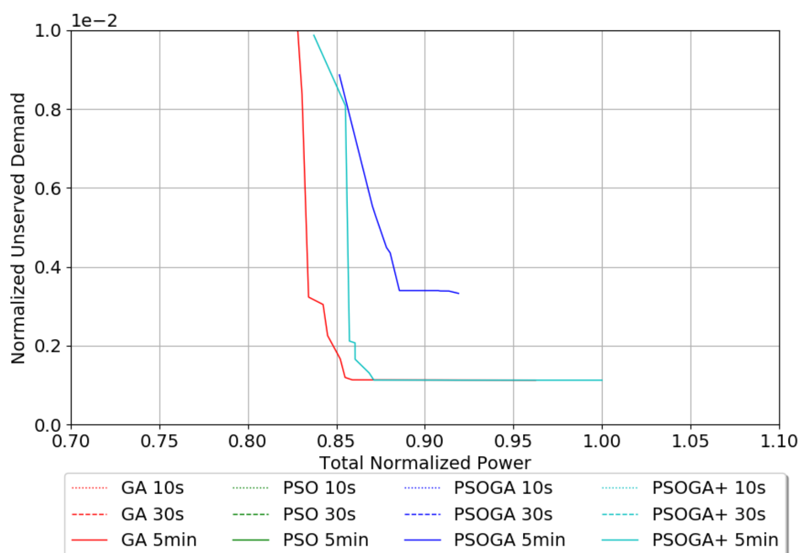


(b) Zoomed

Figure B.2: Scenario 2, 9h timestamp, Pareto Front for Low demand

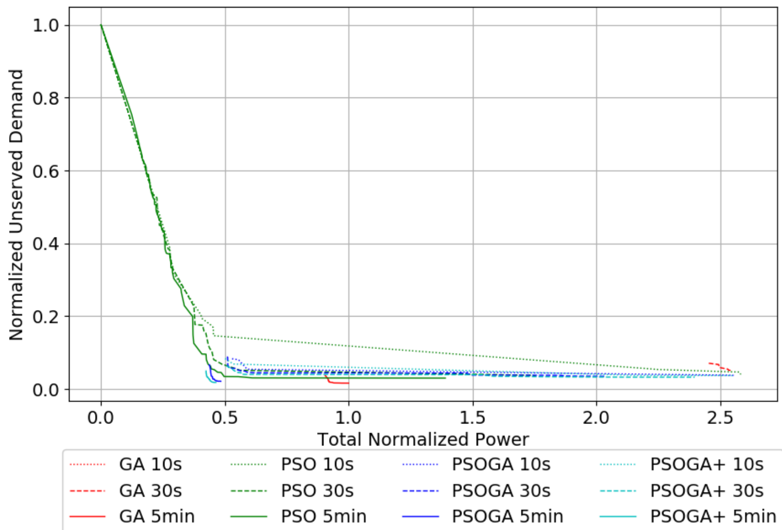


(a) Original

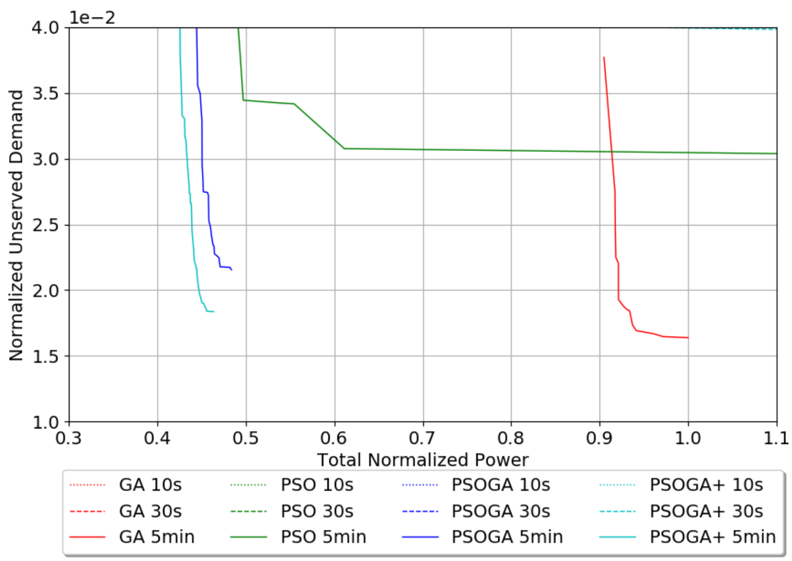


(b) Zoomed

Figure B.3: Scenario 2, 18h timestamp, Pareto Front for Low demand

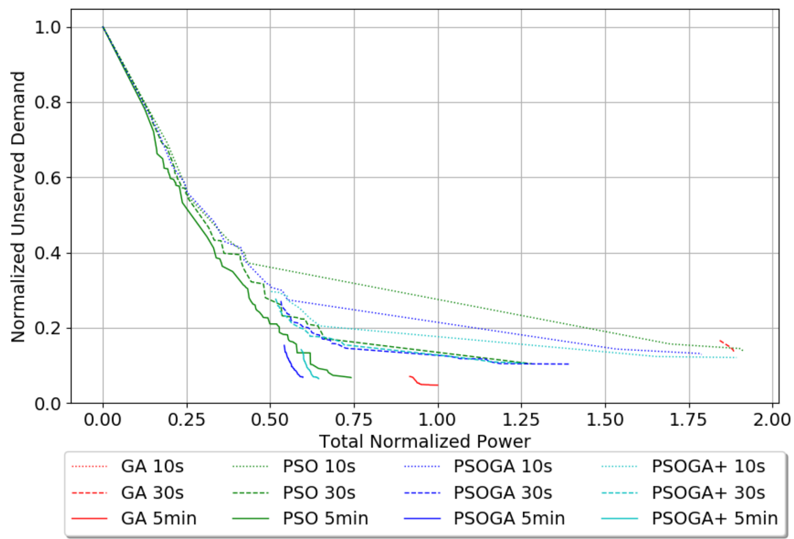


(a) Original

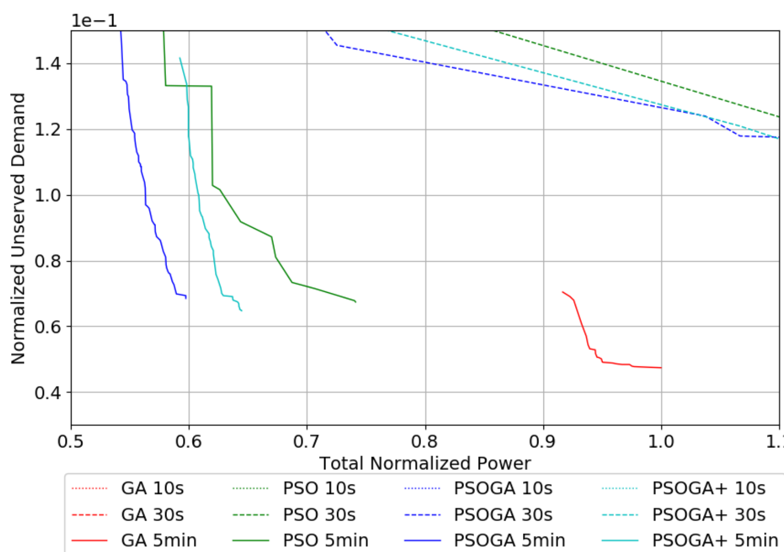


(b) Zoomed

Figure B.4: Scenario 2, 0h timestamp, Pareto Front for Balanced demand

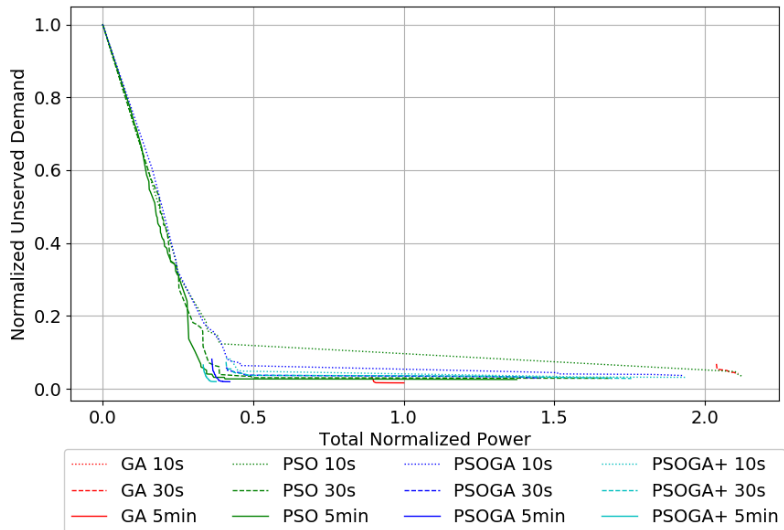


(a) Original

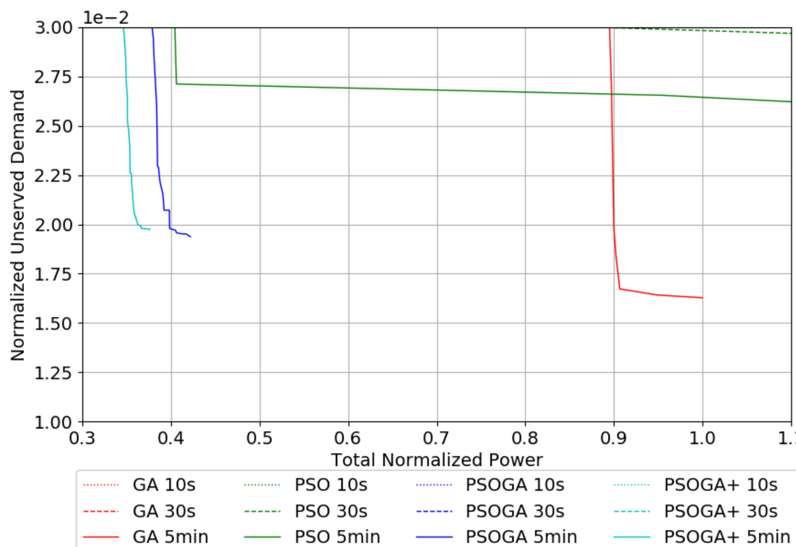


(b) Zoomed

Figure B.5: Scenario 2, 9h timestamp, Pareto Front for Balanced demand

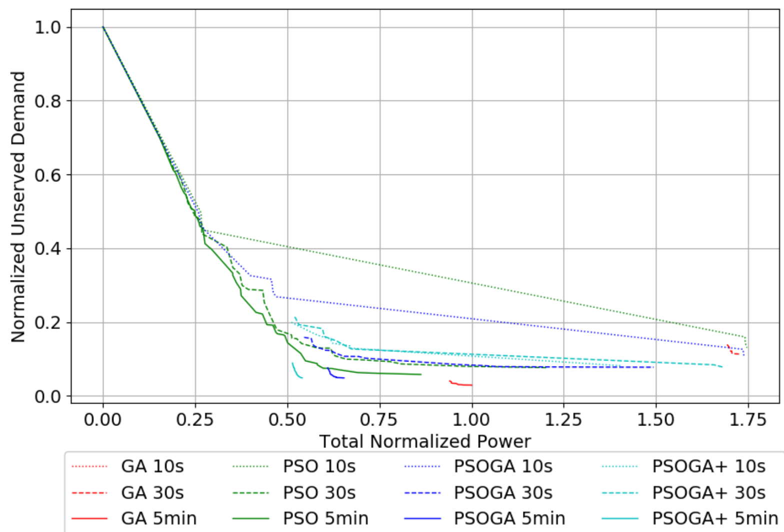


(a) Original

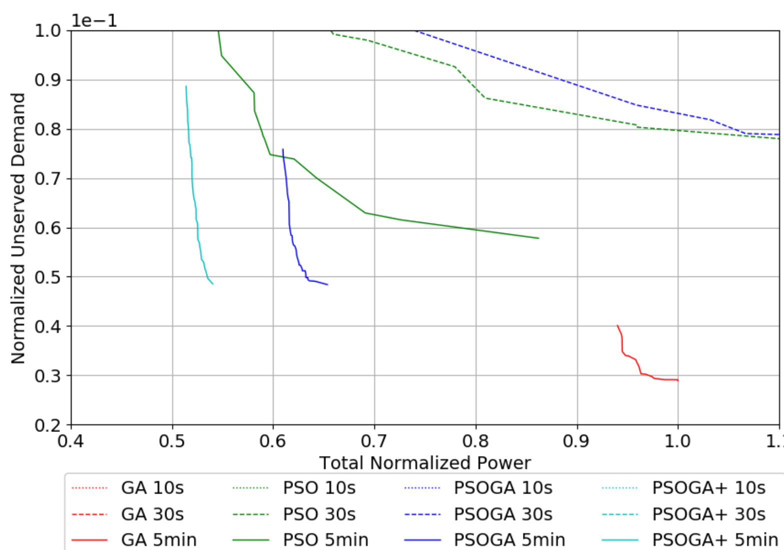


(b) Zoomed

Figure B.6: Scenario 2, 18h timestamp, Pareto Front for Balanced demand

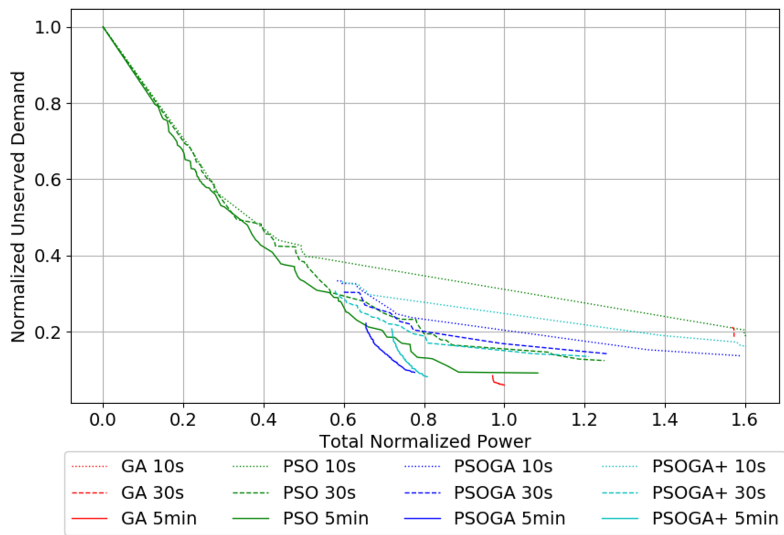


(a) Original

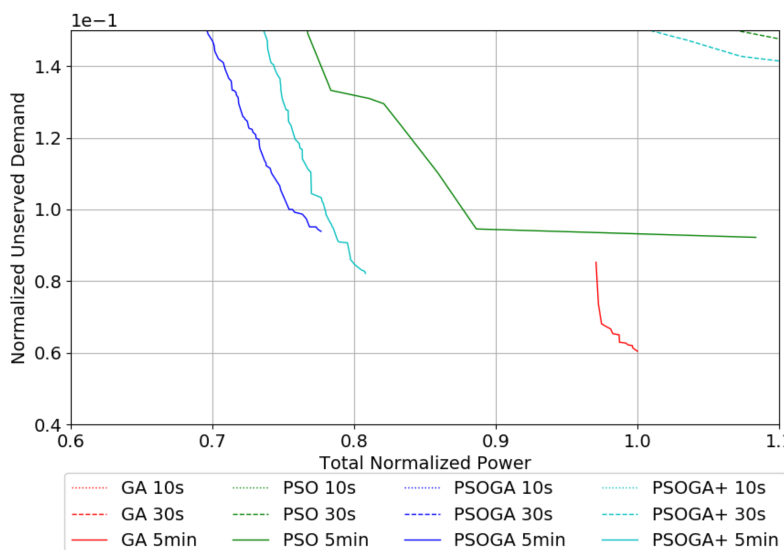


(b) Zoomed

Figure B.7: Scenario 2, 0h timestamp, Pareto Front for Excess demand

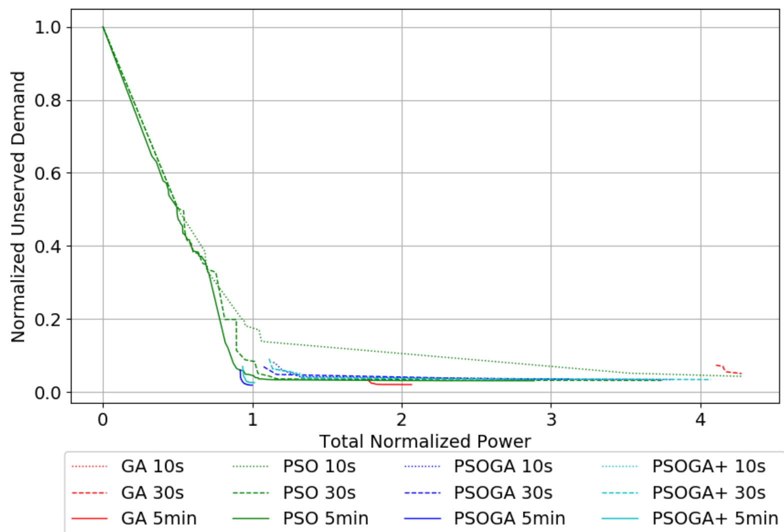


(a) Original

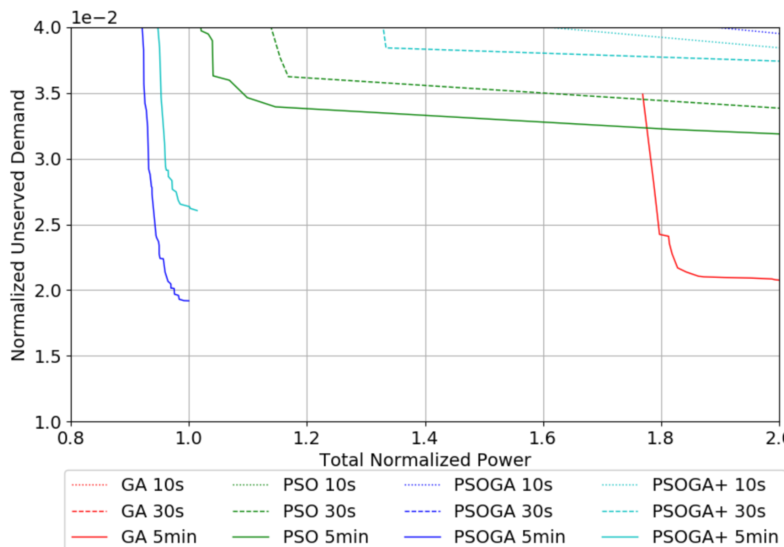


(b) Zoomed

Figure B.8: Scenario 2, 9h timestamp, Pareto Front for Excess demand



(a) Original



(b) Zoomed

Figure B.9: Scenario 2, 18h timestamp, Pareto Front for Excess demand

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